



Mobile Phones as Cognitive Systems

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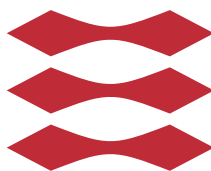
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Mobile Phones as Cognitive Systems

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Summary (English)

Driven by the ubiquitous availability of data and inexpensive data storage, our ability to sense human beings has increased dramatically. Big data has permeated the public discourse and led to surprising insights across the sciences and the humanities. This dissertation presents research on expanding our capabilities in collecting, handling, processing, and using data collected about human beings to create an integrated view of social systems. The goal of the thesis has been threefold.

The first part of the thesis focuses on the need, design, and implementation of large-scale sensor-driven human data collection studies. Social networks can be measured with high resolution and on multiple channels, such as face-to-face meetings, social networks, or phone calls, in order to generate a more comprehensive picture of social systems. The largest study to date measuring large-scale social system—the Copenhagen Networks Study—is described, together with motivation and challenges of the deployment. Preliminary results are presented, indicating how a possibly biased and incomplete picture can be generated when data are collected from a single channel and with a low resolution, thus emphasizing the importance of the proposed approach and deployed implementation.

The second part of the thesis deals with expanding our capabilities to sense the cognitive and emotional state of the users through development of a system for mobile brain imaging—the Smartphone Brain Scanner. A developed framework allows for EEG data collection and processing. It also provides the ability to build end-user applications on top of raw data and extracted features using off-the-shelf and custom-built neuroheadsets and mobile devices, thereby

potentially becoming another channel in integrated human sensing. The motivation for creating such system is presented, advanced data processing—3D source reconstruction—is explained, and applications and use-cases are discussed.

In the third part, the privacy issues surrounding the handling of such sensitive behavioral and biomedical data are investigated. A comprehensive review of best privacy practices in sensor-driven human data collection is presented and recommendations for practitioners are made. Based on this review and experiences with the Copenhagen Networks Study and the Smartphone Brain Scanner, the concept of Living Informed Consent is presented, which postulates larger participant control over collected data for the benefit of users, researchers, and society at large. The same privacy principles are applied to a personal neuroinformatics context, resulting in a proposed new approach to sensitive EEG data handling.

Resumé (Dansk)

Drevet af den øgede tilgængelighed af data samt den lave pris på datalagring, er vores mulighed for at indsamle data om mennesker steget dramatisk. “Big data” har gennemsyret den offentlige diskurs og ført til overraskende indsigter på tværs af naturvidenskab og humaniora. Denne afhandling beskæftiger sig med data indsamlet om mennesket og præsenterer forskning der udvider vores kompetencer indenfor indsamling, håndtering, forarbejdning og anvendelse for at skabe et samlet billede af sociale systemer. Målet med denne afhandling er tredelt.

Den første del af denne afhandling fokuserer på sensor-drevet indsamling af data og diskuterer behovet, designet, samt implementeringen af denne type studier. Sociale netværk kan måles med høj opløsning og via flere kanaler, såsom ansigt-til-ansigt møder, online netværk eller telefonopkald. For at få et fyldestgørende billede af mennesket skal man dække alle vore kommunikationskanaler. Udfordringer samt motivationen bag den til dato største indsamling af sensor-dreven data, med titlen Copenhagen Networks Study, bliver beskrevet og diskuteret. Foreløbige data bliver præsenteret og indikerer udfordringen i bias og muligheden for slutninger baseret på ufuldstændige data fra kun en kanal. Dette understreger betydningen af den beskrevne fremgangsmåde.

Den anden del af denne afhandling omhandler et nyt mobilt system, kaldet Smartphone Brain Scanner, der udvider vores nuværende rammer til mobilt at kunne registrere kognitive tilstande hos mennesker. Den udviklede metode gør det muligt at både indsamle og behandle EEG data dynamisk. Yderligere, åbner den muligheder for at brugere selv kan bygge og anvende nye applikationer på det indsamlede data. Metoden er både kompatibel med standard-

komponenter, specialbyggede neuro-headset samt andre mobile enheder og kan dermed potentielt blive en ny kanal i indsamlingen af data om mennesket. Denne del beskriver motivationen bag skabelsen af systemet, forklarer de avancerede databehandlingsmetoder og giver eksempler på hvorledes et sådant system kan være nyttigt.

I den tredje del undersøges og diskuteres håndteringen af disse følsomme data med henblik på beskyttelsen af privatlivets fred. En omfattende gennemgang belyser de nuværende fremgangsmåder og giver detaljerede anbefalinger til fremtidige studier der omhandler anvendelse af denne slags personfølsomme data. Baseret på denne gennemgang og de to projekter: Copenhagen Networks Study og Smartphone Brain Scanner introduceres begrebet Living Informed Consent. Her postuleres at større individuel kontrol over data er til gavn for brugere, forskere og samfundet generelt. De samme principper om privatlivets fred anvendes i sammenhængen med personlig neuroinformatik og resulterer i en ny tilgang til håndtering af følsomme EEG data.

Preface

This thesis was prepared at the Department of Applied Mathematics and Computer Science at the Technical University of Denmark (DTU) in partial fulfillment of the requirements for acquiring the Ph.D. degree in engineering.

The thesis consists of a summary report and a collection of one book chapter, four published scientific papers, and four upcoming papers. The work was carried out between 2011 and 2014.

Lyngby, 31-March-2014

A handwritten signature in black ink, consisting of a stylized 'A' followed by a long, sweeping horizontal line that ends in a small upward flick.

Arkadiusz Stopczynski

List of Publications

Papers included in the thesis

[A] Daniel Greenwood, **Arkadiusz Stopczynski**, Brian Sweatt, Thomas Hardjono, and Alex Pentland. Institutional Controls: The New Deal on Data (Book Chapter). *Big Data, Privacy, and the Public Good: Frameworks for Engagement*. Edited by Julia Lane, Victoria Stodden, Stefan Bender, and Helen Nissenbaum. Cambridge University Press, 2014. Hardback ISBN 9781107067356; paperback ISBN 9781107637689.

[B] **Arkadiusz Stopczynski**, Vedran Sekara, Piotr Sapiezynski, Andrea Cuttone, Mette My Madsen, Jakob Eg Larsen, and Sune Lehmann. Measuring Large-Scale Social Networks with High Resolution. *Under Review in PLOS ONE*. arXiv preprint arXiv:1401.7233 (2014).

[C] Yves-Alexandre de Montjoye, **Arkadiusz Stopczynski**, Erez Shmueli, Alex ‘Sandy’ Pentland, and Sune Lehmann. The Strength of the Strongest Ties in Collaborative Problem Solving. *Under Review in Scientific Reports* (2014).

[D] **Arkadiusz Stopczynski**, Carsten Stahlhut, Michael Kai Petersen, Jakob Eg Larsen, Camilla Falk Jensen, Marieta Georgieva Ivanova, Tobias S. Andersen, and Lars Kai Hansen. Smartphones as pocketable labs: Visions for mobile brain imaging and neurofeedback. *International Journal of Psychophysiology*, Volume 91, Issue 1, January 2014, Pages 54-66, ISSN 0167-8760, doi:10.1016/j.ijpsycho.2013.08.007.

[E] Michael Kai Petersen, Carsten Stahlhut, **Arkadiusz Stopczynski**, Jakob Eg Larsen, and Lars Kai Hansen. Smartphones get emotional: mind reading images and reconstructing the neural sources. In *Affective Computing and Intelligent Interaction*, pp. 578-587. Springer Berlin Heidelberg, 2011.

[F] **Arkadiusz Stopczynski**, Carsten Stahlhut, Jakob Eg Larsen, Michael Kai Petersen, and Lars Kai Hansen. The Smartphone Brain Scanner: A Portable Real-time Neuroimaging System. *PLoS ONE* 9(2): e86733. doi:10.1371/journal.pone.0086733.

[G] Carsten Stahlhut, Hagai Thomas Attias, **Arkadiusz Stopczynski**, Michael Kai Petersen, Jakob Eg Larsen, and Lars Kai Hansen. An evaluation of EEG scanner's dependence on the imaging technique, forward model computation method, and array dimensionality. *Engineering in Medicine and Biology Society (EMBC)*, 2012 Annual International Conference of the IEEE, pp. 1538-1541. IEEE, 2012.

[H] **Arkadiusz Stopczynski**, Riccardo Pietri, Alex Pentland, David Lazer, and Sune Lehmann. Privacy in Sensor-Driven Human Data Collection: A Guide for Practitioners. arXiv preprint arXiv:1403.5299 (2014).

[I] **Arkadiusz Stopczynski**, Dazza Greenwood, Lars Kai Hansen, Alex Pentland. Privacy for Personal Neuroinformatics. arXiv preprint arXiv:1403.2745 (2014).

Additional papers not included in the thesis

[J] **Arkadiusz Stopczynski**, Jakob Eg Larsen, Carsten Stahlhut, Michael Kai Petersen, and Lars Kai Hansen. A smartphone interface for a wireless EEG headset with real-time 3D reconstruction. *Affective Computing and Intelligent Interaction*, pp. 317-318. Springer Berlin Heidelberg, 2011.

[K] Jakob Eg Larsen, Piotr Sapiezynski, **Arkadiusz Stopczynski**, Morten Mørup, Rasmus Theodorsen. Crowds, Bluetooth, and Rock'n'Roll: Understanding music festival participant behavior. *Proceedings of the 1st ACM International Workshop on Personal Data Meets Distributed Multimedia*. New York, NY, USA: ACM, PDM '13, pp. 11–18. doi:10.1145/2509352.2509399.

[L] Camilla Birgitte Falk Jensen, Michael Kai Petersen, Jakob Eg Larsen, **Arkadiusz Stopczynski**, Carsten Stahlhut, Marieta Georgieva Ivanova, Tobias Andersen, and Lars Kai Hansen. Spatio temporal media components for neurofeedback. *In 2013 IEEE International Conference on Multimedia and Expo (ICME)*.

[M] Camilla Birgitte Falk Jensen, Marieta Georgieva Ivanova, **Arkadiusz Stopczynski**, Michael Kai Petersen, Tobias Andersen, and Carsten Stahlhut. Training your brain on a tablet. *34th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*.

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To my Parents with Love.

You are co-authors of all my work.

Contents

| | |
|--|------------|
| Summary (English) | i |
| Resumé (Dansk) | iii |
| Preface | v |
| List of Publications | vii |
| Acknowledgments | ix |
| 1 Introduction | 3 |
| 1.1 Motivation | 4 |
| 1.2 Thesis Outline and Contributions | 6 |
| 2 Mobile Devices, Big Data, and Society | 13 |
| 2.1 Data Revolution | 14 |
| 2.2 Living Labs | 17 |
| 3 Mobile Brain Imaging | 25 |
| 3.1 Data Acquisition | 26 |
| 3.2 Data Processing | 30 |
| 3.2.1 Filtering | 30 |
| 3.2.2 Artifact Removal | 32 |
| 3.2.3 Source Reconstruction | 34 |
| 3.3 Applications | 38 |
| 3.3.1 Brain-Computer Interfaces | 39 |
| 3.3.2 Cognitive & Emotional State Decoding | 41 |
| 3.3.3 Neurofeedback | 45 |

| | | |
|----------|---|------------|
| 4 | Privacy of Personal Data | 53 |
| 4.1 | Personal Data System | 54 |
| 4.2 | Living Informed Consent | 58 |
| 5 | Future Outlook | 65 |
| 5.1 | Large-Scale Sensor Driven Human Data Collection | 66 |
| 5.2 | Personal Brain Imaging | 67 |
| 5.3 | Privacy of Personal Data | 68 |
| 6 | Conclusions | 73 |
| A | Institutional Controls: The New Deal on Data | 79 |
| B | Measuring large-scale social networks with high resolution | 101 |
| C | The Strength of the Strongest Ties in Collaborative Problem Solving | 147 |
| D | Smartphones as pocketable labs: Visions for mobile brain imaging and neurofeedback | 167 |
| E | Smartphones get emotional: mind reading images and reconstructing the neural sources | 183 |
| F | The Smartphone Brain Scanner: A Portable Real-time Neuroimaging System | 197 |
| G | An Evaluation of EEG Scanner's Dependence on the Imaging Technique, Forward Model Computation Method, and Array Dimensionality | 211 |
| H | Privacy in Sensor-Driven Human Data Collection | 219 |
| I | Privacy for Personal Neuroinformatics | 261 |
| | Bibliography | 283 |

CHAPTER 1

Introduction

This opening chapter serves as a general introduction to the work contained in the thesis.

Section 1.1 describes a motivation for the use of mobile phones as cognitive systems and presents challenges addressed in the remainder of the thesis, while Section 1.2 gives a chapter-by-chapter overview, including a brief summary of the scientific papers.

1.1 Motivation

Over the last few years, our ability to collect and analyze data about human behavior has increased dramatically. This development has been partially driven by individuals posting and storing data about themselves and friends using on-line social networks (such as Facebook or Twitter) or by collecting their data for self-tracking purposes (quantified-self movement). Data regarding human behavior is also collected through the environment: embedded RFIDs, cameras, traffic monitoring, business transactions. Across the sciences, researchers conduct studies collecting data at an unprecedented resolution and scale. Using computational power combined with mathematical models, such rich datasets can be mined to infer underlying patterns, thereby providing insights into human nature.

Data about human behavior and our cognitive and emotional states, have been historically collected in many domains, including psychology, sociology, and neuroscience, to name just a few. With the increased ability to collect quantitative data from large populations, over long periods of time, and with many bits per user, a new domain of computational social science has been born [LPA⁺09]. Although technical and methodological advancements make data collection, handling, and analysis possible, there are still many questions to answer and boundaries to push, especially in increasing the quality and scale of the collected data, introduction of new sophisticated channels for integrated sensing, and addressing privacy of the participants in the presence of such sensitive linked data.

The aim of the work contained in this thesis has been to address some of the most pressing challenges in collection of large-scale sensor-driven human data, primarily for research purposes. The first addressed challenge was the need to expand the scale of the human data collection. We used mobile devices (smartphones) as sociometers, specifically by: sensing participants' location, face-to-face interactions, calls and text messages, interactions in online social networks. Similar studies have been conducted by groups from various research institutions, notably MIT [API⁺11, EP06], Dartmouth College [MLF⁺08], Aalto University [KN11], and Nokia Research Center in collaboration with École Polytechnique Fédérale de Lausanne [KBD⁺10]. In a natural evolution of this previous work, this thesis describes the efforts to increase the number of participants, the period of data collection, and the number of bits collected per user to an unprecedented level. Such expansion makes it possible to answer novel questions about social systems, such as understanding how different observed channels may generate different views of the system, how and why networks evolve, and what drives creation and collapse of communities. The resulting deployment—the Copenhagen Networks Study [SSS⁺14] (Appendix B)—is a testbed, a living lab allowing for multiple studies and experiments to be devel-

oped, in addition to the basic observational study, as postulated in [GSS⁺14] (Appendix A). The initial results presented in this thesis indicate that there is in fact a pressing need to address the challenges of incomplete data, irregular sampling, and low number of channels and participants in living lab deployments. Results presented in [dMSS⁺14] (Appendix C) show how our sensing capabilities, combined with an experimental setup, can be used to gain insights into human nature—illustrating the importance of strong ties in collaborative problem solving. Knowing the structure of the friendships both within and between groups of students working on study assignments, we showed that performance is correlated with the number of ties. However, the effect is strongly non-linear—only the strongest ties are significant. The friendships were collected as self-reports but also recovered from the campus wifi system, showing how sensed social structure can be linked to performance in problem solving.

The cognitive state of the user, recovered from brain activity, has been classically considered separately from the behavioral traces. Brain activity can be measured using various methods, including functional Magnetic Resonance Imaging (fMRI), Positron Emission Tomography (PET), Magnetoencephalography (MEG), Electroencephalography (EEG), and Functional near-infrared spectroscopy (fNIR). The experiments involving measuring brain activity have been almost exclusively done in a tightly-controlled laboratory setting, approaching the brain as an input-output system, with precisely synchronized stimuli evoking measurable responses. While it is not feasible to move most of the methods for recording brain activity outside of the lab due to the equipment complexity (fMRI, PET, MEG), EEG can be used in more naturalistic contexts. Only recently have we witnessed EEG moving outside of the laboratory, with the arrival of low-cost user-oriented neuroheadsets [DVGD13], powerful mobile devices, and software frameworks for data acquisition and analysis. These developments offer an unprecedented opportunity for sensing cognitive states of the participants in more naturalistic settings, for working with larger populations and over extended periods of time, and for building novel user-facing applications on top of the extracted features. EEG can be used in many contexts, prominently for Brain-Computer Interfaces (BCI) in explicit (voluntary user control) [QHMST13] and implicit (cognitive state monitoring) [LBJ⁺99] modes or in assistive technologies [MRMP⁺10]. The vision of using mobile devices coupled with low-cost neuroheadsets as ‘pocketable labs’ is outlined in [SSP⁺13] (Appendix D). The architecture of the framework developed as part of this vision—the Smartphone Brain Scanner—is presented in [SSL⁺14] (Appendix F), together with the description of custom-built hardware (EEG cap) and technical validation of the system. An important method implemented in the developed software is source reconstruction, in which the signal measured by scalp electrodes is mapped to the original sources in the brain volume. Results presented in [SAS⁺12] (Appendix G) indicate valid source reconstruction can be performed even with a low number of electrodes. The results from source reconstruction are shown in

the context of reconstructing responses to emotional stimuli in [PSS⁺11] (Appendix E). Although the framework is still in development and the presented results focus primarily on validation in standard lab paradigms, the developed approach to portable and mobile brain imaging is a significant step towards integrated human sensing, where the cognitive and emotional state of the user becomes another channel in large-scale human data collection studies, such as the Copenhagen Networks Study.

As our sensing capabilities grow and we use more advanced channels, collecting more bits per user, for longer periods, and for larger populations, it becomes even more important to address the privacy of the users in a way that considers the size and complexity of the collected data and used methodologies. Although the concept of protecting the privacy and well-being of human participants is not new, some commonly used practices—when closely analyzed—do not necessarily live up to expectations in massive sensor-driven human data collection. An extensive overview of the employed privacy practices, from a both technical and legal perspective, is given in [SPP⁺14] (Appendix H). The conclusion is that the most pressing issue to address is how informed consent is handled. This informs the proposed concept of Living Informed Consent, in which the user is encouraged to understand and control data sharing through the entire lifetime of the data collection effort. The resulting requirement of reducing dimensionality of the shared data, in order to make the sharing comprehensible for the user is both used in the Copenhagen Networks Study and outlined in a personal neuroscience context in [SGHP14] (Appendix I).

1.2 Thesis Outline and Contributions

In addition to the current chapter, the thesis consists of five introductory chapters, one book chapter, four published papers, and four upcoming papers. The papers are found in the appendices and constitute the main contribution of the thesis. The introductory chapters aim to provide motivation for sensor-driven human data collection and provide an overview of the Copenhagen Networks Study deployment, introduce components of the Smartphone Brain Scanner framework in terms of data collection, processing, and applications, and, finally, to outline the developed privacy approaches. In summary, the remainder of the thesis is structured as follows:

Chapter 2, Mobile Devices, Big Data, and Society, provides a foundation for the rest of the thesis. The Big Data revolution and its impact on society are explained. The concept of living labs is introduced and an outline of the Copenhagen Networks Study deployment is provided.

Chapter 3, Mobile Brain Imaging, presents the challenges in sensing cognitive and emotional state of users. Collected brain activity is considered an additional channel in integrated human sensing, and the presented challenges include data collection, processing, and application. EEG data processing methods are briefly introduced.

Chapter 4, Privacy of Personal Data, focuses on the privacy of the users participating in integrated sensitive data collection efforts. Concepts of Personal Data System (PDS) and Living Informed Consent are introduced and their applicability in sensor-driven human data sensing is explained.

Chapter 5, Future Outlook, outlines future developments that can extend the work presented in this thesis.

Chapter 6, Conclusions, recapitulates the main findings presented in the thesis.

Paper A, Institutional Controls: The New Deal on Data [GSS⁺14], explores the emergence of the Big Data society, arguing that the ‘personal data sector’ of the economy needs productive collaboration between research institutions, government, private sector, and citizens to create new markets. It envisions data access governed by Living Informed Consent, in which users are entitled to know what data are being collected about them by which entities, empowered to understand the implications of data sharing, and finally put in charge of the sharing authorizations. The need for better data collection, processing, and sharing practices is explained and the establishment of a New Deal on Data is discussed, grounded in principles, such as the opt-in nature of data provision, the boundaries of the data usage, and parties accessing the data.

Paper B, Measuring Large-Scale Social Networks With High Resolution [SSS⁺14], describes the deployment of a large study designed to collect data about human interactions and movements with unprecedented temporal resolution and depth, both in terms of duration and number of distinct channels, creating a living lab as envisioned in [GSS⁺14]. The data are collected using state-of-the-art smartphones as social sensors and include face-to-face interactions, telecommunication, social networks, location, and background information for a densely connected and coherent population of 1 000 individuals—the Copenhagen Networks Study. Based on the preliminary results, it is shown how a possibly biased and incomplete view of the system can be generated when data are collected just from a single channel and with a low resolution, thus emphasizing the importance of the proposed approach and deployed implementation.

Paper C, The Strength of the Strongest Ties in Collaborative Problem Solving [dMSS⁺14], reports on how the self-reported and sensed friend-

ship networks correlate with group performance in collaborative complex problems solving. Using experimental data collected within the Copenhagen Networks Study framework [SSS⁺14], it is shown that while groups' performance is strongly correlated with their networks of expressive and instrumental ties, only the strongest ties in both networks have an effect on performance. Both networks of strong ties explain more of the variance than other factors such as measured or self-evaluated technical competencies or personality of the group members. These results have consequences for the organization of groups of scientists, engineers, or other knowledge workers solving complex problems.

Paper D, Smartphones as pocketable labs: Visions for mobile brain imaging and neurofeedback [SSP⁺13], outlines how mobile brain imaging solutions, such as the Smartphone Brain Scanner, may expand our capability to sense human cognitive and emotional state. Normally subject to physical constraints in labs, neuroscience experimental paradigms can be transformed into dynamic environments allowing for the capturing of brain signals in everyday contexts, by integrating with living labs such as the Copenhagen Networks Study [SSS⁺14]. Using smartphones or tablets to access text or images may enable experimental design capable of tracing emotional responses when shopping or consuming media, incorporating sensorimotor responses reflecting our actions into brain machine interfaces, and facilitating neurofeedback training over extended periods.

Paper E, Smartphones get emotional: mind reading images and reconstructing the neural sources [PSS⁺11], presents a realization of vision from [SSP⁺13], showing how emotional responses reflected in different scalp potentials when viewing pleasant and unpleasant pictures can be distinguished using a fully portable EEG system. Clustering independent components across subjects, it is possible to remove artifacts and identify common sources of synchronous brain activity, consistent with earlier findings based on conventional EEG equipment. Applying a Bayesian approach to reconstruct the neural sources not only facilitates differentiation of emotional responses but may also provide an intuitive interface for interacting with a 3D rendered model of brain activity.

Paper F, The Smartphone Brain Scanner: A Portable Real-time Neuroimaging System [SSL⁺14], presents the technical details and validation of Smartphone Brain Scanner for building multi-platform, portable EEG applications with real-time 3D source reconstruction. Benefits and challenges are discussed, including technical limitations and details of real-time reconstruction of brain activity. Examples of brain activity captured in a simple experiment involving imagined finger tapping are presented, showing that the acquired signal in a relevant brain region is similar to that obtained with standard EEG lab equipment. Although the quality of the signal in a mobile solution using

an off-the-shelf consumer neuroheadset is lower than the signal obtained using high-density standard EEG equipment, it is proposed that mobile application development may offset the disadvantages and provide completely new opportunities for neuroimaging in natural settings.

Paper G, An Evaluation of EEG Scanner’s Dependence on the Imaging Technique, Forward Model Computation Method, and Array Dimensionality [SAS⁺12], presents a comparison of a low and high density EEG setup’s dependence on correct forward modeling. Specifically, it is examined how different forward models affect the source estimates obtained using four inverse solvers: Minimum-Norm, LORETA, Minimum-Variance Adaptive Beamformer, and Sparse Bayesian Learning. The results indicate that useful 3D reconstruction is possible even with low-dimensionality setup, such as the one used in mobile solution of the Smartphone Brain Scanner [SSL⁺14].

Paper H, Privacy in Sensor-Driven Human Data Collection: A Guide for Practitioners [SPP⁺14], provides a survey of the work related to addressing privacy issues in research studies collecting detailed sensor data on human behavior. Reflections on the key problems and recommendations for future work are included. A concept of Living Informed Consent is introduced, arguing for larger end-user control over collected data in research and various other contexts. This comprehensive guide for practitioners—co-authored with pioneers of the field—provides a unique perspective and frame of reference for the emerging large-scale sensor-driven human data collection studies, based on the experiences with the Copenhagen Networks Study [SSS⁺14] and the Smartphone Brain Scanner [SSL⁺14].

Paper I, Privacy for Personal Neuroinformatics [SGHP14], deals with the challenges of collecting EEG data from large populations, in linked databases, and over long periods of time. Human brain activity collected in the form of Electroencephalography (EEG), even with low number of sensors, is an extremely rich signal. Traces collected from multiple channels and with high sampling rates capture many important aspects of participants’ brain activity and can be used as a unique personal identifier, similarly to fingerprints, DNA, or a portrait. The motivation for sharing EEG signals is significant, as a means to understand the relation between brain activity and well-being, or for communication with medical services. An integration of a personal neuroinformatics system, the Smartphone Brain Scanner [SSL⁺14], with a general privacy framework openPDS, used in the Copenhagen Networks Study [SSS⁺14], is proposed. It is shown how raw high-dimensionality data can be collected on a mobile device, uploaded to a server, and subsequently operated on and accessed by applications or researchers, without disclosing the raw signal.

CHAPTER 2

Mobile Devices, Big Data, and Society

Over the last few years, our ability to collect and analyze data about human behavior has increased dramatically. Using computational power combined with mathematical models, rich datasets can be mined to infer underlying patterns, thereby providing insights into human nature. This development has had a significant impact on how the science is done and on the society at large.

This chapter presents a concise overview of the Big Data revolution and its impact on society and research practices. Section 2.1 serves as a general introduction to the developments of data collection, handling, and use. Section 2.2 outlines the concept of living labs—large long-lasting studies of sensor-driven human data collection. The novel contributions of this thesis are highlighted at the end of each section.

2.1 Data Revolution

Sustaining a safe, healthy, and efficient society has been one of the major challenges of mankind. The rapid urban growth caused by the Industrial Revolution of the 1800s has created new problems, remedied temporarily by the creation of centralized networks for delivering clean water and safe food, removing waste, providing energy, facilitating transportation, etc. These networks formed the backbone of society as we know it today.

Today, we live in societies experiencing another rapid growth, enabled by increased computation power and connectivity. We routinely communicate across countries and continents—exchanging ideas, making plans, and working together. Our societies are denser and live faster than ever before, and the increased production, consumption, and interconnectivity create both great opportunities and dramatic problems. We face the challenges of global warming, uncertain energy, water, and food supplies, and a rising population and urbanization that will, for example, add 350 million people to the urban population by 2025 in China alone [WMD⁺09]. Over the course of a year, in just one small district of Los Angeles, vehicles looking for parking places can create the equivalent of 38 trips around the world, burning 47 000 gallons of gasoline and producing 730 tons of CO_2 [Sho06]. Epidemics can be very difficult to stop in a highly connected world—modeled as scale-free networks—as the critical threshold of spreading λ_c below which the virus would die naturally, takes the value of 0 [PSV01]. With a zero threshold, while a reduced spreading rate decreases the virus' prevalence, eradication is not guaranteed [DB02]. Thus, from a theoretical perspective, viruses spreading on a scale-free network—in the modern world—may seem unstoppable.

The static systems of the past are increasingly inefficient in dealing with the problems of today. We have to build systems within a control framework that can sense the situation, combine observations with models of demand and dynamic reaction, and use the resulting predictions to tune their behavior. Such responsive systems will create the nervous system of the society, allowing us to both research the phenomena and react to them in real-time. The engine driving the creation of these systems is Big Data—massive amounts of data available about virtually all aspects of human life. Many of these data are created as digital breadcrumbs we all leave behind as we move through the world, such as call records, GPS location fixes, and credit card transactions [LPA⁺09]. These data may be very different from what we decide to put on Facebook or Twitter, when we choose both what to tell other people and what persona we want to create. Significant amounts of these data are created through always-connected mobile devices. Those devices—smartphones, and more recently tablets—follow their users everywhere, feature a rich set of embedded sensors, offer continuous

connectivity, and, for many users, have become the preferred way of interacting with the virtual or even physical world. Large percentages of populations in developed countries carry smartphones, making them capable of sensing and being sensed in various ways. In developing countries, where the penetration of advanced smartphones is lower, the feature phones are still becoming immensely popular [Puh13]; although the hardware is less advanced, feature phones and the interactions they facilitate can still be captured and analyzed, for example Call Detail Records or mobile payments history. For the first time in history we can start quantitatively mapping the behavior of entire populations with unprecedented resolution and scale.

Mining these breadcrumbs has allowed researchers to come up with important insights, about both fundamental human nature and practical implications for improving society. For example, in the Data for Development (D4D) challenge based on CDRs, one team developed a model for how disease spreads in a country and demonstrated that information campaigns based on one-to-one phone conversations among members of social groups can be an effective countermeasure [LDDPM13]. The epidemics of influenza can be predicted from search data, where aggregating over billions of noisy queries can extract a signal of early symptoms becoming prominent in certain areas [GMP⁺09]. Or influence in social networks can be monitored and understood, giving us insight into fundamental mechanics of human societies [AW12]. The list continues.

Although we have learned and continue to learn so much, it is only the beginning of the journey and there are still significant obstacles in unleashing the full potential of big data. One of the most significant problems nowadays is how data are siloed—collected and used exclusively within single companies, organizations, and units of governments. This causes the vast majority of conducted research to use a single channel for understanding human behavior and we may not know how much bias is introduced because of it, particularly in case of highly-interconnected data such as social networks. We intuitively know that people communicate over multiple channels, effortlessly switching between face-to-face interactions, phone calls, and emails. Similarly, data sampling—uneven in many big data studies—may create biases. CDRs, for example, only provide data when users actively engage, by making or receiving a phone call or SMS. Further, CDRs are typically provided by a single provider with some finite market share. If the market share is 20% of the population and we consider only links internal to the dataset, this translates to only 4% of the total number of links, assuming random network and random sampling [OSH⁺07]. Uneven sampling not only reduces the quality of available data, but also—maybe more importantly—may lead to selection bias when choosing users to include in the analysis. When only high-frequency voice-callers are chosen from CDR dataset for the purpose of analysis, the randomness of participants' behavior may be overestimated [RZZB12]. Similarly, choosing users with a large network and

many interactions on Facebook may lead to overestimation of diversity in the ego-networks [MLC⁺13]. Every time we discard a significant number of users, we risk introducing a bias in the data. Highly uneven sampling that cannot be corrected with redundant data, compels the researcher to make mostly arbitrary choices as part of the analysis, complicating subsequent analysis, especially when no well-established ground truth is available to understand the bias.

Not only data themselves are siloed, but also many of the research domains face challenges in working together to create a comprehensive view of human nature and social systems. Neuroscience, psychology, and sociology have been, to date, variably successful in producing and using big data and integrating it into interdisciplinary studies. Neuroscience, for example, has been classically focused primarily on tightly-controlled experiments in the lab, making it a challenge to integrate collected data with available behavioral data from naturalistic settings. Enabling interdisciplinary research through data and methods sharing is an important part of expanding our research potential.

The insights and knowledge generated from big data have been very important. Still, many challenges have to be addressed to accelerate the progress of research and its impact on society. Doing so is extremely important for addressing the challenges we face today on a global scale.

Contribution of the thesis

To realize the promise of a big data society and to reduce the potential risk to individuals, the operational frameworks governing the business, legal, and technical dimensions of organizations must be updated. In [GSS⁺14] (Appendix A) we showed how the New Deal on Data [Pen09] can be used today, within existing institutions, as a driving force for changing data practices. We outlined the operational framework from business, legal, and technical (BLT) perspectives—a novel approach to integrated modeling of system solutions—showing how the current siloed data can be opened for the benefit of society. We described our efforts to understand the technical means of its implementation, the legal framework around it, its business ramifications, and the direct value of the greater access to data that it enables. It is clear that companies must play the major role in implementing the New Deal, incentivized by business opportunities, guided by legislation, and pressured by demands from users. Only with such orchestration it will be possible to modernize the current system of data ownership and to put the immense quantities and capabilities of collected personal data to good use.

2.2 Living Labs

To unleash the full potential of our sensing capabilities, computation power, and mathematical models, we need new ways to collect and analyze human data. One way to approach the existing challenges is to build living laboratories—longitudinal studies on large populations embedded in the real world and with multiple channels observed. Universities are a natural environment for the first deployments of such testbeds, with large densely-connected populations, an existing trust relation between participants and institution, diversity of evolving social interactions, and a certain stability of population as the participants go through their study years.

In terms of size, the living labs deployed to date involve at most 100-200 participants. Although such populations are definitely sufficient for creating important insights, the effective number of active users in the datasets may vary significantly over time, due to the natural tendency of users to drop out from the studies or data collection mechanisms failing, as shown in Figure 2.1. We can note in the Copenhagen Networks Study [SSS⁺14] (Appendix B) that the 2012 deployment matched the Friends and Family study from MIT [API⁺11] in terms of the population size (with the exception of a single-day server crash in April), and the 2013 deployment (still in its early stages while this thesis is being written) set a new standard for the size of in-depth studied populations. Part of the living labs approach is longitudinal studies. To date, most of the deployments captured up to a year of data from any particular population. In the Copenhagen Networks Study, users from 2012 are being transitioned to the 2013 deployment, giving us the possibility to continue studying the original population while extending the coverage of the social system by adding more participants.

The living labs approach postulates observing populations on multiple channels, to obtain the most comprehensive view of social interactions, mobility, and human behavior. Such integrated sensing seeks to describe the participants and their relations in multiple dimensions, enabling a multi-disciplinary approach to research. For example, both online and face-to-face interactions may be important in information spreading, but only face-to-face network is significant for the spread of epidemics. Those two networks may be very different even in the same population, as shown in Figure 2.2. Adding more channels, even beyond the normally used behavioral ones, such as brain activity recordings, is only possible when those can be efficiently linked with each other. This leads to user-centric sensing, where multiple data types describe the user and her interactions. As described in the Privacy chapter, such linked datasets may have significant implications for participants' privacy.

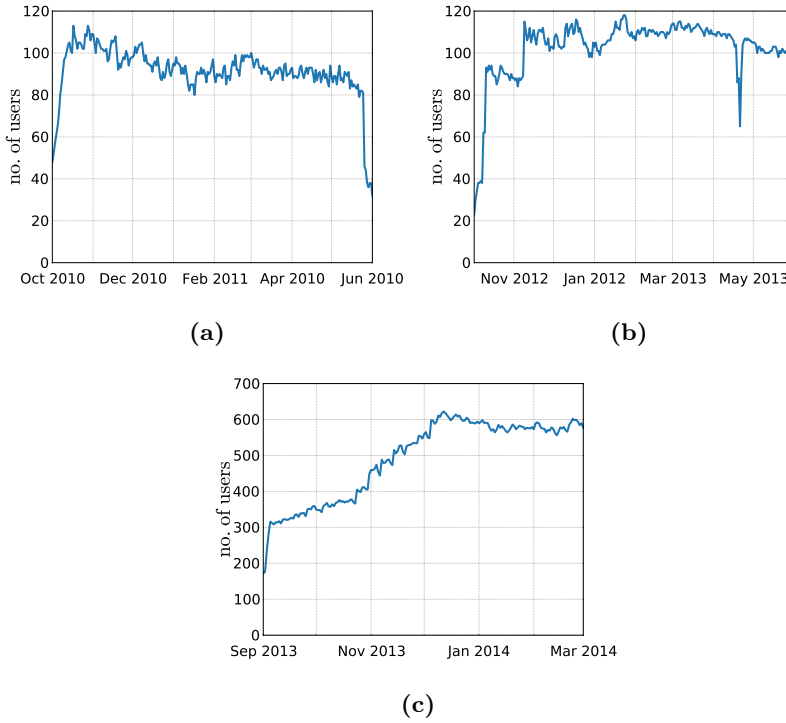


Figure 2.1: Number of active users in (a) Friends and Family dataset from MIT, with “the highest quality among all our [MIT Human Dynamics] mobile data” [API⁺11] and—included in this thesis—Copenhagen Networks Study (b) 2012 and (c) 2013 [SSS⁺14]. We can note variable number of active users, with a general tendency to drop later in the studies due to participants quitting and data collection mechanisms failing.

An important aspect of living labs is the opportunity to deploy experiments on top of the existing user base, technical architecture, and collected data. This approach is very different from using exclusively pre-existing datasets, without possibility to alter users’ behavior, where the data might have been collected during usual operation, before the idea of the study had even been conceived (e.g. CDRs, Wifi logs), or the access to the data might have not been granted before a single frozen and de-identified dataset was produced. Within living labs, we are able to run controlled experiments, including surveys distributed via the smartphone software. We can for example divide participants into subpopulations and expose them to distinct stimuli, addressing the topic of causality as well as confounding factors, both of which have proven problematic [Lyo11, ST11] for



Figure 2.2: Face-to-face and online activity. Figure shows data from the Copenhagen Networks Study 2013 deployment for one representative week. **Online:** Interactions (messages, wall posts, photos, etc.) between users on Facebook. **Face-to-Face:** Only the most active edges, which account for 80% of all traffic, are shown for clarity. **Extra Info. F2F:** Extra information contained in the Bluetooth data shown as the difference in the set of edges. **Extra Info. Online:** Additional information contained in the Facebook data. From [SSS⁺14] (Appendix B).

the current state of the art [FC08, CF09]. We can also test how the spread of a disease changes the behavior of the social system, by making the participants aware of a virtual germ spreading, rather than researching the spread based solely on an unchanged, healthy behavior [LDDPM13]. Or, we can understand how assigning people into working groups with different social connectivity influences their performance, as we showed in [dMSS⁺14] (Appendix C).

Contribution of the thesis

The Copenhagen Networks Study described in [SSS⁺14] (Appendix B) is the largest established living lab to date, in terms of population size, observed channels, and interdisciplinary collaboration as compared to most notable examples of [API⁺11, KN11, AN10]. The described motivation and architecture pushes the boundaries of how sensor-driven human data collection can be realized. The results from the study—although still preliminary—clearly indicate how important it is to observe multiple channels of human communication and mobility to create a comprehensive view of social systems. For example, we showed how we can successfully use Wifi channel as a noisy proxy for face-to-face interactions, in addition to commonly used Bluetooth sensing. Or, more importantly, we showed how a single social system can look significantly different when observed on different channels, a result with implications for how we model social systems. Sensing such systems can give us many insights into fundamental human na-

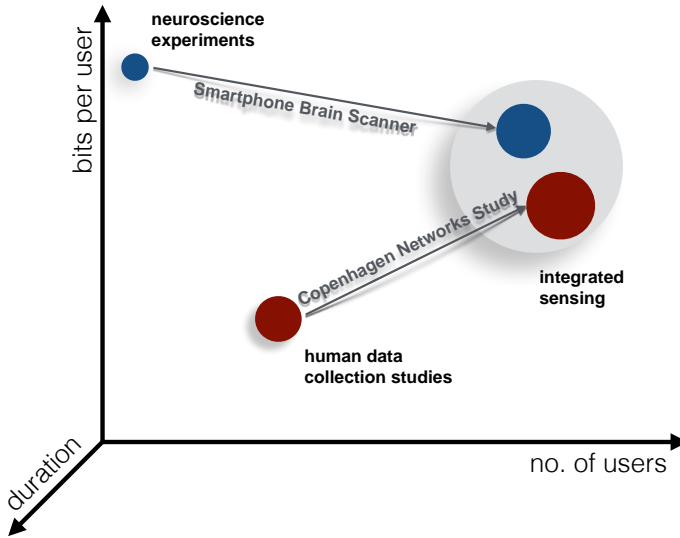


Figure 2.3: Advancements in human sensing with two approaches described in this thesis. The Smartphone Brain Scanner intended for low-cost long-lasting brain imaging in naturalistic settings, with lower number of electrodes and more noise introduced due to less-controlled environment. The Copenhagen Networks Study building on existing human data collection studies, with significantly increased number of participants, duration, and collected bits per user. As discussed in the Future Outlook chapter, the frameworks can be used for integrated human sensing, providing a more comprehensive image of the users and social systems.

ture and have practical implications for how we run our society. In [dMSS⁺14] (Appendix C) we reported that while groups' performance is strongly correlated with their networks of expressive and instrumental ties (self-reported and sensed), only the strongest ties in both networks have an effect on performance. This strong non-linearity of the effect has important implications for how we understand collaborative problem solving and how we design the working environments for the most skilled workers.

The technical solution developed for 2013 deployment of the Copenhagen Networks Study is a cutting-edge re-usable implementation of open Personal Data System (openPDS) [dMWP12]. Based on standards, such as OAuth 2.0 and OpenID 2.0, it enables not only core data collection and deployment of experiments, but also research on a wide variety of privacy solutions, such as

privacy-preserving data sharing or Living Informed Consent. The entire system is built around end-user consent and grant of authorizations to integrated data. We found that putting such a strong emphasis on the end-user is a necessary approach for living lab deployments of this size and complexity.

Figure 2.3 shows the approach taken in this thesis to expanding sensor-driven human data collection. Taking two domains of sensing humans—behavior and cognitive & emotional state—as a starting point, the goal was to expand them in the three dimensions of bits collected per user, duration, and population size. In the Copenhagen Networks Study, we significantly increased the signal collected for the users (introducing new channels and increasing the resolution of the existing ones) and increased the number of observed users several times. Although the study is still in relatively early stages, we are able to transition users from 2012 deployment into the 2013 platform, and expect to continue growing the study while maintaining the existing population, pushing the boundary of longitudinal approach. In the Smartphone Brain Scanner, described in the next chapter, we started with existing systems and paradigms of classical neuroscience, featuring very rich signal, but small populations and short periods, and extended the possible number of users and duration by introducing low-cost mobile user-friendly EEG framework. Even though the signal obtained in recordings in naturalistic settings has lower effective bitrate, due to inherent noise and lower number of electrodes, such setup can be integrated with collection of behavioral data, creating an comprehensive view of the participants.

Establishing the Copenhagen Networks Study as a living lab allowed numerous projects and Bachelor’s and Master’s thesis to be completed. The Master’s thesis, both in progress and completed, include: Søren Dalsgaard Ulrikkeholm *Architecture of a Large-Scale Sociometer Project*, Ana Martić *Predictability of Human Behavior using Mobility and Rich Social Data*, Martin Metz *Sensing and Visualizing Smartphone App Usage Behavior*, Luis Fernando Flores Vargas *Mining spatial knowledge from large scale deployment of distributed mobile sensors*, Asger Johansen *Graph Databases for Massive Multilayered Social Data*, Thomas Kraina *Distributed Social Sensing on Smartphone Platforms*, Constantin Teodor Gherghescu *Inferring Pairwise Co-location from Noisy Bluetooth Signals*, Albert Fernandez de la Peña *Data Visualization for Informed Consent*, Georgios Chatzigeorgakidis *A Mobile Lifelog for Multilayer Data*, Marta Malgorzata Magiera *Visualizing Human Mobility*, Jeppe Lind Andreassen *Experience and Interaction Sampling in a Large-Scale Mobile Sensing Environment*, Lasse Valentini Jensen *Measuring Information Propagation in Complex Networks*, to name just the most relevant ones.

Mobile Brain Imaging

With recent developments in portable EEG hardware, increasing computation power of mobile devices, and advancements in data processing algorithms it has become possible to perform advanced brain scanning in naturalistic conditions. Experiments recording the cognitive state of the users can be done on large populations and over long periods, providing new insights into human nature, especially when combined with behavioral data sources.

This chapter outlines the problem of mobile brain imaging. Section 3.1 focuses on challenges in data acquisition, from both software and hardware perspectives. Section 3.2 describes important methods in EEG data processing, including artifact removal and source reconstruction of brain activity. Finally, Section 3.3 gives examples of applications that can be realized on top of an acquired and processed EEG signal.

3.1 Data Acquisition

The research communities studying human behavior have, in recent years, gained access to an unprecedented sensing and computational power that can fit into a pocket. These developments have enabled the building of inexpensive specialized research tools, such as sociometer badges [CP03], as well as the emergence of more powerful and novel consumer-grade devices. Today, smartphones and tablets are capable of sensing, processing, transmitting, and presenting complex information; this has already had a significant impact on many research domains, including social science [API⁺11], mobile sensing [JLJ⁺10], and computer-human interaction [BRS11]. Similarly, these devices can open up new possibilities in neuroscience, where the need for mobility and portability—systems that support quantitative measurements in natural settings—has been widely recognized [MGJ⁺09, BTV⁺10, GGF⁺11].

Capturing brain activity through EEG with low-cost wireless neuroheadsets has only recently become possible and may relocate neuroimaging from constrained laboratory settings to experimental paradigms, allowing us to model mental state of the participants in an everyday context. Until recently, neuroimaging experiments were almost exclusively performed with participants who were at rest, under the assumption that the measurement of brain responses should not be influenced by participants sitting or laying down. However, animal studies using mice show that neurons in the visual cortex double their visually evoked firing rates if the mice run on a treadmill rather than stand still [NS10], indicating that this assumption may be inaccurate. Or, since the discovery of parietal–frontal circuits of mirror neurons—firing both when we grasp an object and when we observe others doing the same [PFF⁺92, GFFR96]—the sensorimotor system should no longer be considered as only involved with motion. These mechanisms should rather be understood as forming an integral part of cognition, allowing us to generalize the goals of actions based on motor representations in the brain [RS10].

In addition to the already existing literature concerned with dynamic brain states during natural complex stimuli in conventional laboratory experiments [HNL⁺04, BZ04, DSDP12], there has been a growing call to create studies relaxing the constraints of the lab in order to understand how we perceive our surroundings under naturalistic conditions [MGJ⁺09]. By adding even a few degrees of freedom, it may be possible to understand how brain activity changes when simply changing posture [SHCN08], either by measuring how theta activity is attenuated in sleepy subjects once they stand up [CPC03] or by analyzing the modulation in spectral power within alpha and beta bands when one foot hits the ground and the other is lifted [GGMF11]. Natural motion has been incorporated into laboratory experiments in order to correlate motion capture data

with the brain responses being triggered [GGF⁺11]. Debener and colleagues recently demonstrated how a P300 experiment can be moved outside of the lab by combining the wireless hardware from a consumer neuroheadset with standard EEG cap electrodes and using a laptop to record the cortical responses, thus creating a portable lab stored in a backpack and easily carried by the participants [DME⁺12].

Several consumer-grade EEG products (neuroheadsets) are built based on a single dry electrode with a reference and ground attached to a headband—based on the ThinkGear module manufactured by NeuroSky—and provide analog-digital (A/D) conversion and amplification of a single EEG channel. Such a simple single-electrode setup may give the ability to measure mental concentration and drowsiness by assessing the relative distribution of brainwave frequencies [Yas09]. A more sophisticated consumer neuroheadset—Emotiv EEG—provides both wireless communication and A/D conversion of 14 EEG channels at a 128 Hz sampling rate. Originally designed as a mental game controller based on simple BCI paradigms, extraction of cognitive state, and facial expressions, the majority of electrodes are placed over the frontal cortex without midline positions. This setup is suboptimal for many research paradigms and is prone to muscle artifacts. It is, however, possible to merge the wireless hardware from the Emotiv neuroheadset with high quality, conductive, gel-based electrodes in a standard EEG cap, as originally demonstrated by Debener et al. [DME⁺12] and further developed in [SSL⁺14] (Appendix F). By repackaging the electronics and battery into a small box (49mm × 44mm × 25mm) and attaching them to an EEG cap that had been rewired to 16 sintered Ag/AgCl ring electrodes (14 channels + reference and ground), a fully customizable montage can be realized. This allows the electrodes to be freely placed according to the 10–20 international system.

Mobile and portable EEG data acquisition poses challenges from a software perspective as well. Among the primary problems are synchronization of the events in the system and optimization for processing with low-latency—a concern especially relevant in mobile devices, as they feature non-real-time operating systems and execution frameworks not tweaked for real-time performance (e.g. Dalvik virtual machine in Android, pausing the execution due to garbage collection). Figure 3.1 shows the response timings in the Smartphone Brain Scanner system while it is running on different platforms. The delays between the signal reaching the EEG headset (either off-the-shelf Emotiv EEG or custom-built cap) and the device responding to the signal (changing screen color, measured by a photocell) are between 80 and 140 ms on the tested devices. Such delays make it feasible to build real-time applications on top of data acquisition; small jitter (deviation in the response time) allows for good synchronization with presented stimuli and other external events.

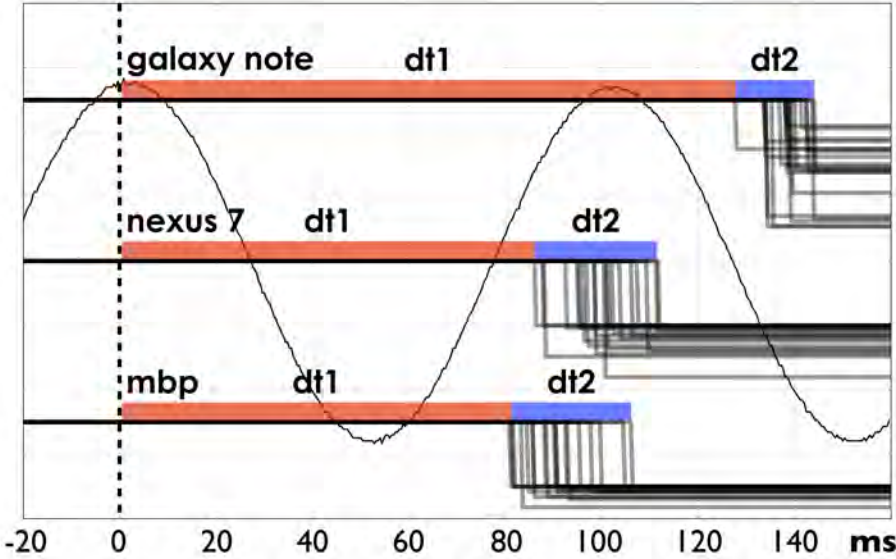


Figure 3.1: Smartphone Brain Scanner response timings. The system responds to the sinusoid signal peak (time 0). The red color ($dt1$) indicates minimal observed delay; the blue color ($dt2$) indicates jitter. Galaxy Note running Android 4.0.1, 60 Hz AMOLED screen, $dt1 = 125ms$, $dt2 = 16ms$; Nexus 7 running Android 4.1.1, 60 Hz IPS LCD screen, $dt1 = 85ms$, $dt2 = 26ms$; MacbookPro, LCD screen (60 Hz), $dt1 = 80ms$, $dt2 = 26ms$. From [SSL⁺14] (Appendix F).

Contribution of the thesis

Although the need for mobility and portability in a neuroscience context has been widely recognized, the effort to build extensible and advanced frameworks for naturalistic brain scanning has been limited so far. This thesis presents work on the Smartphone Brain Scanner, a framework for mobile real-time stimulus delivery, data acquisition, and processing using off-the-shelf consumer-grade equipment. The framework, which includes software running on mobile and desktop platforms as well as custom-built EEG cap hardware, has been validated in regards to low-level data acquisition, signal quality, and processing as presented in [SSL⁺14] (Appendix F).

Smartphone Brain Scanner is built in Qt (a C++ framework) rather than in

prevalent data analysis environments such as MATLAB. It approaches the problem of portable brain activity collection as a smartphone sensing challenge, enabling new types of contributions to neuroscience. The Human-Computer Interaction (HCI) community is already applying consumer-grade neuroheadsets to extend existing paradigms, as in [VS12]. The availability of low-cost equipment results in general ‘hacker-and-tinkerers’ audiences gaining interest in using neuroscience tools, for an example see <http://neurogadget.com>. There is a great value in the emerging potential of entirely new groups of researchers and developers becoming interested in neuroscience and obtaining tools allowing them to develop new kinds of applications. For those reasons, Smartphone Brain Scanner was built in an extensible way, with the architecture presented in Figure 3.2. Several projects have been created on top of the core system, including the Bachelor’s thesis of Kløverpris Sørensen *Synchronizing Mobile Eye Tracking and Neuroimaging on a Smartphone* and the Master’s thesis of Mateusz Ryszard Swirski and Vlad Gelu Luca *Enhancing User Experience by Combining Eye Tracking and Neurofeedback*.

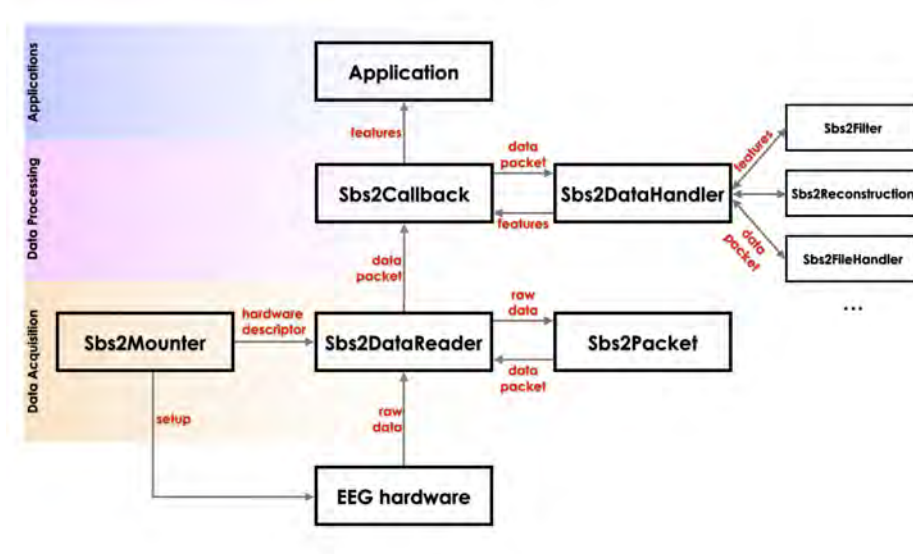


Figure 3.2: The Smartphone Brain Scanner architecture. Data are acquired in the first layer from the EEG hardware, passed to the Data Processing Layer, and extracted. Features, as well as raw values, are then available for applications. From [SSL⁺14] (Appendix F).

Notably, the ability to capture high-quality EEG data on a low-cost, portable, and self-contained device offers new opportunities for medical applications. This

has been recognized by Grand Challenges Canada in a grant awarded to Farrah J. Mateen, **Arkadiusz Stopczynski**, Chenchu Dorji, Marco Carone, and Laurent Benedetti entitled *A smartphone EEG to diagnose seizure disorders in Bhutan* (Grant # 0338-04 (2013), \$270 000). The goal of the project is to utilize the Smartphone Brain Scanner in low-income settings for diagnosing mental disorders, specifically epilepsy. The project website is available at <http://www.bhutanbrain.com>.

This thesis presents the design, implementation, and evaluation of the first fully portable 3D EEG imaging system, including both custom-made software and hardware. The open source software allows for real-time EEG data acquisition and source imaging on standard off-the-shelf Android mobile smartphones and tablets with a good spatial resolution and frame rates in excess of 40 fps. The evaluation showed the combined system provides for a stable imaging pipeline with a delay of 80–140 ms. Future developments in hardware and software will allow for even better signal acquisition and analysis from low-density and mobile setups, making it possible to add sensed brain activity as another channel in integrated human sensing.

3.2 Data Processing

EEG signal is rarely useful directly after acquisition; many methods can be used in order to process and extract features from the raw data. Some of them, such as filtering or artifact removal, are useful for improving signal-to-noise ratio (SNR) by removing (electrical) noise both generated by subjects and found within the environment. Other methods, such as Independent Component Analysis (ICA) or source reconstruction, can be used to learn about brain processes generating the measured signal, rather than working with the measurements directly. In this section, three techniques of data processing are outlined—filtering, PCA-based artifact removal, and source reconstruction. All the described methods are suitable for real-time data processing on devices with constrained computation power and have been successfully implemented for the real-time processing in the Smartphone Brain Scanner.

3.2.1 Filtering

In the EEG measurement, the brain activity is collected based on the electrical signal generated primarily in the cortex. This activity is composed of multiple frequencies, divided into bands (e.g. alpha bands between 8 and 16 Hz); these

bands are related to different processes occurring in the brain. The environment where the recordings are performed may contain a significant amount of electrical noise, which decreases the quality of the recorded signal. The electrical signal may also be generated by various physiological processes within the participant. A simple way to reduce such noise is to use filtering, which removes frequencies outside of the desired band. Even a simple linear filter can make the interpretation and subsequent processing of the EEG signal easier, especially when used in a real-time context [NMC98].

Figure 3.3 shows the effect of a simple bandpass filter (8-30 Hz, alpha & beta EEG bands) applied to a real-time signal directly on a mobile device running the Smartphone Brain Scanner EEG Viewer application. The unfiltered signal contains a significant noise, around 50 Hz, caused by an electrical alternating current present in the environment (in the US we would observe a peak around 60 Hz). This line-frequency contamination is not necessarily of a constant phase, amplitude, or frequency, which prevents the simplest subtractive filters from being entirely effective [Eri88]. When the higher frequencies are not considered for analysis, however, this noise can be filtered out with a simple bandpass filter. High-pass filters are typically used to remove slow artifacts, such as those coming from the electrical conductance of the skin or movement. Low-pass filters are commonly applied to remove high-frequency artifacts, such as electromyographic (EMG) signals produced by skeletal muscles. The filtering presented here is carried out as a convolution between the input signal and the filter coefficients, using finite impulse response (FIR) filters. The FIR filter is described by the equation:

$$y[n] = b_0x[n] + b_1x[n-1] + \cdots + b_Nx[n-N] = \sum_{i=0}^N b_i x[n-i] \quad (3.1)$$

where $x[n]$ and $y[n]$ are input and output signals respectively, and b_i are filter coefficients. N denotes the filter order; the impulse response of the filter lasts for $N+1$ samples and then settles to 0. FIR filter can be useful in an EEG context due to its simple implementation in software, relatively easy computation (for small orders), and feed-forward nature. As the filter does not use the previous results for the next calculations (no feedback), the rounding errors do not sum up over time; the filter is also guaranteed to be stable.

In the simple implementation in the Smartphone Brain Scanner framework we use static pre-computed filter coefficients, loaded from a file depending on the filter order and filtered band. For the common operations we use $N = 32$, meaning that the 33 newest samples are used in filtering and the effective introduced delay of 16 samples (125 ms with 128 Hz sampling rate), acceptable for

many real-time applications. The coefficients for various orders and bands were generated and exported from the Matlab environment, using `fir1()` function. The static FIR filter is one of the simplest filters implementation-wise; however, more sophisticated solutions may be useful in the mobile EEG context, while still being computationally feasible. An example could be an adaptive filter capable of self-adjustment due to being driven by an error signal, such as a notch filter (removing a narrow band, useful for filtering electrical noise) based on the least mean squares algorithm with a variable step-size parameter [OBM05].

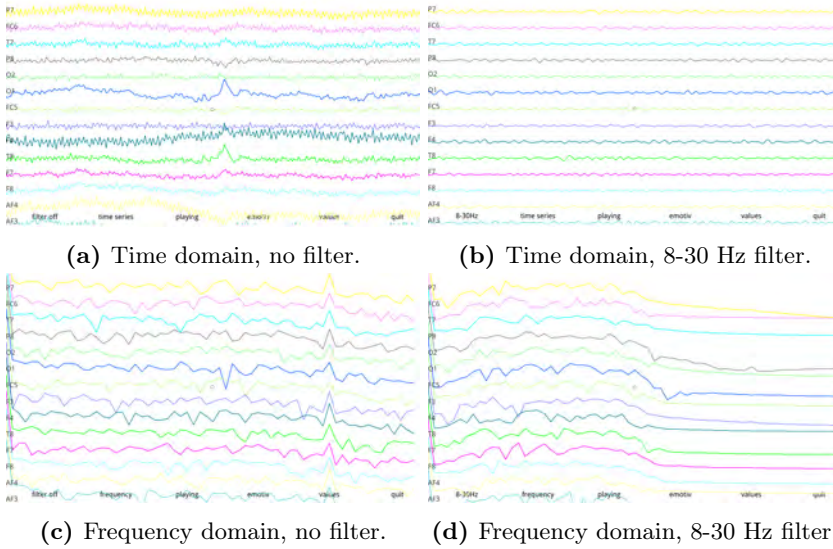


Figure 3.3: Simple bandpass filtering with Smartphone Brain Scanner. When activated, the filter removes frequencies outside of 8-30 Hz band, with the effect visible both in time and frequency domains. The signal component of 50 Hz, caused by electrical devices in the environment, is removed.

3.2.2 Artifact Removal

Artifacts in EEG data can be caused by blinks, eye-movements, muscle noise, line noise, and cardiac signals, and pose a significant challenge in EEG analysis and interpretation. This challenge is even more pronounced when the recordings are performed in naturalistic settings with systems that have a low number of electrodes. Eye blinks, measured with Electrooculography (EOG), are one of the most common sources of artifacts in the signal, can last up to 400 ms, and have an amplitude an order of magnitude larger than electrical signal originat-

ing in cerebral cortex [BP11]. Removing artifacts in a computationally simple way, and in real-time, is challenging. One of the well researched approaches is to decompose the signal into components—for example using Principal Component Analysis (PCA) or Independent Component Analysis (ICA)—with the assumption that the EEG signal will separate from the artifacts; the artifact components can then be removed and the signal can be reconstructed using only the EEG components.

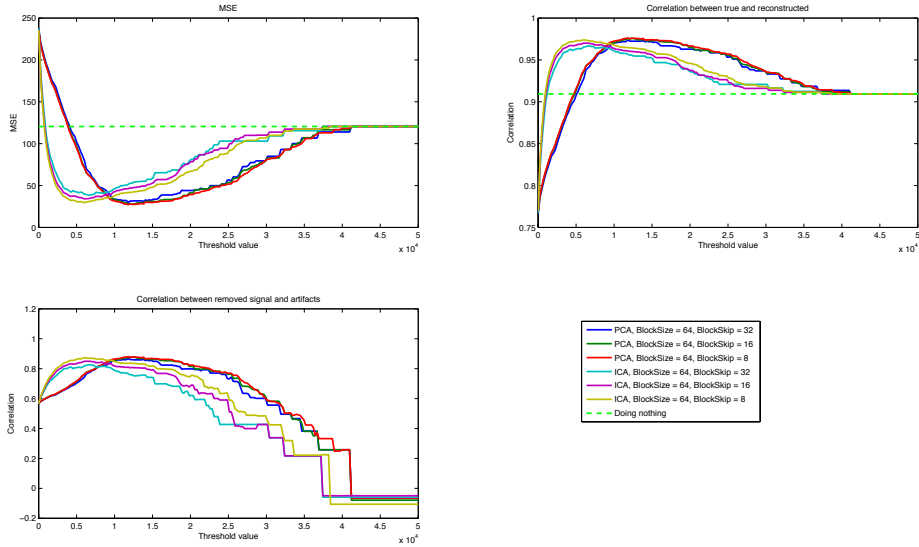


Figure 3.4: Comparison of MS-ICA and PCA-based artifact rejection for different threshold values. For a small block size, the performance of ICA and PCA are similar, although for different rejection threshold values and with different sensitivity to this parameter. Courtesy of Michael Riis Andersen.

In general cases, it has been shown that an ICA-based artifact removal performs better than a PCA-based one, effectively separating and removing artifacts even with an amplitude comparable to an EEG signal [JHL⁺98, JMH⁺00]. The ICA-based methods, however, tend to be of higher computational complexity, making computationally simple methods for real-time artifact removal interesting. In a project related to the Smartphone Brain Scanner, Michael Riis Andersen compared Molgedey and Schuster ICA (MS-ICA) [MS94] (a variant of ICA with a closed form solution, which is much faster than conventional ICA methods) with PCA for real-time artifacts removal—specifically eye blinks—for different block sizes of the analyzed signal. The artifact components were identified by computing variance and comparing it to a threshold value, a reasonable approach

for eye blink, as they feature amplitude significantly higher than an EEG signal. MS-ICA was found to outperform PCA for large block sizes—a result consistent with the literature—but for small block sizes, suitable for real-time processing due to a smaller introduced delay, the performance of MS-ICA and PCA was found to be similar. This is depicted in Figure 3.4, which shows the performance of the PCA-based artifact rejection for a small block size of 64 packets is comparable to the ICA-based method, although for different rejection threshold values and with different sensitivity to the choice of the parameter. Since the algorithm is intended to be used in a real-time setting, small block sizes are desirable to avoid introducing large delays.

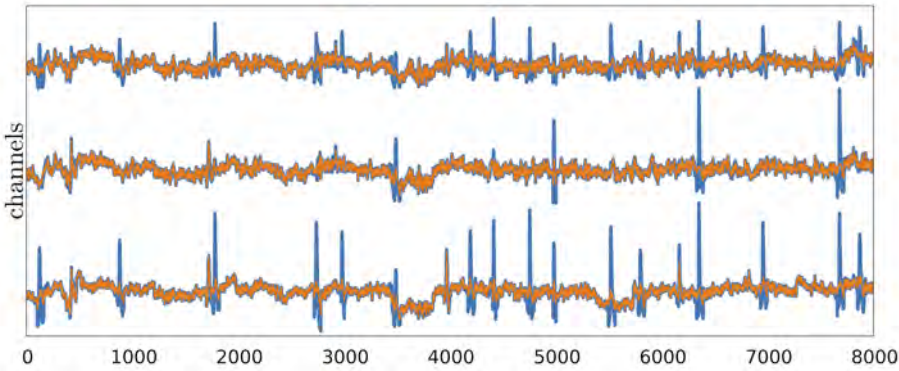


Figure 3.5: Raw (blue) EEG signal from 3 channels with blink artifacts clearly visible as spikes. Orange signal shows the signal with artifacts removed, using PCA with block size of 64, block skip of 8, and optimal threshold parameter. Courtesy of Michael Riis Andersen.

This work clearly shows that with relatively simple and computationally efficient methods some common artifacts can be removed in real-time on mobile devices. An initial implementation of the PCA-based artifact rejection has been done for the Smartphone Brain Scanner, and the method has been tested on both synthetic and real EEG data. The implementation is currently in development, awaiting inclusion in the stable branch of the framework.

3.2.3 Source Reconstruction

Source reconstruction is a method of estimating the sources of electrical current within the brain most likely to have generated the EEG signal observed at scalp level. The forward problem, as depicted in Figure 3.6, is the calculation of measurement of the brain activity by a relatively small number of

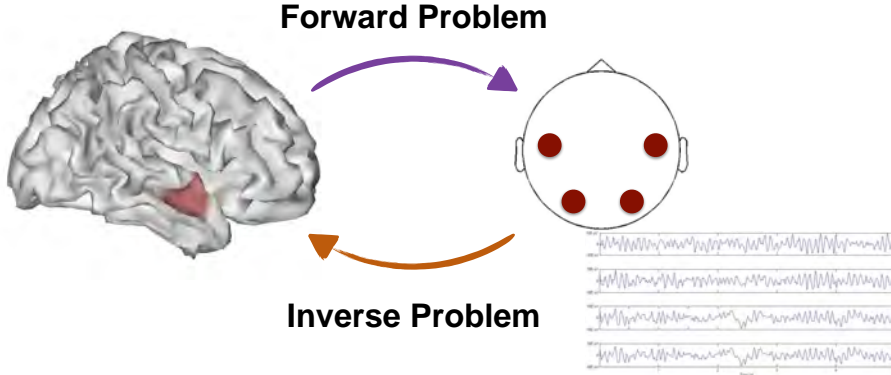


Figure 3.6: Illustration of forward and inverse problem in source reconstruction. The inverse problem of reconstructing brain sources generating the measured signal is extremely ill-posed.

electrodes placed on the scalp. As the number of possible source locations in the brain far exceeds the number of channels used for measurement, the inverse problem of recovering the original brain activity is extremely ill-posed. A unique solution can be obtained by imposing prior information corresponding to anatomical, physiological, or mathematical properties [BG97, PRF02, HI94]. Here, the outlined inverse methods are Bayesian formulations of the widely used Minimum-norm method (MN) [HI94] and Low-Resolution Electromagnetic Tomography (LORETA) [PMML94]. The Bayesian formulation allows adaptation of hyper-parameters to different noise environments in real-time, which is an improvement over previous real-time source reconstruction approaches [CLL06, NKM08, BMG11] that applied heuristics to estimate the parameters involved in the inverse method. The source reconstruction presented here is based on an assumed forward model matrix, \mathbf{A} (channel \times cortical locations), connecting scalp sensor signals \mathbf{Y} (channel \times time) and current sources \mathbf{S} (cortical locations \times time) [BML01]. The term \mathcal{E} accounts for noise not modeled by the linear generative model.

$$\mathbf{Y} = \mathbf{A}\mathbf{S} + \mathcal{E}. \quad (3.2)$$

The estimation of the forward model \mathbf{A} describes how signals originating in the brain volume propagates and reaches the electrodes. It considers various issues, including sensor positions, the geometry of the head model (spherical or ‘realis-

tic' geometry), and tissue conductivity values [WKM⁺07, HVG⁺07, DWD⁺09]. With the forward model \mathbf{A} and the measurement \mathbf{Y} given, and the linear relation in Eq. (3.2), the source generators \mathbf{S} of the signal can be estimated. We assume the noise term $\boldsymbol{\epsilon}$ to be normally distributed, uncorrelated, and time-independent, which leads to the probabilistic formulation:

$$p(\mathbf{Y}|\mathbf{S}) = \prod_{t=1}^{N_t} \mathcal{N}(\mathbf{y}_t | \mathbf{A}\mathbf{s}_t, \beta^{-1}\mathbf{I}_{N_c}) \quad (3.3)$$

$$p(\mathbf{S}) = \prod_{t=1}^{N_t} \mathcal{N}(\mathbf{s}_t | \mathbf{0}, \alpha^{-1}\mathbf{L}^T\mathbf{L}). \quad (3.4)$$

Where $p(\mathbf{S})$ is the prior distribution over \mathbf{S} with \mathbf{L} given as a graph Laplacian ensuring spatial coherence between sources and β^{-1} as the noise variance. Using Bayes' rule, the posterior distribution over the sources is maximized by:

$$\begin{aligned} p(\mathbf{S}|\mathbf{Y}) &= \prod_{t=1}^{N_t} \mathcal{N}(\mathbf{s}_t | \boldsymbol{\mu}_t, \boldsymbol{\Sigma}_s) \\ \boldsymbol{\Sigma}_s &= \alpha^{-1}\mathbf{I}_{N_d} - \alpha^{-1}\mathbf{A}^T\boldsymbol{\Sigma}_y\mathbf{A}\alpha^{-1} \\ \boldsymbol{\Sigma}_y^{-1} &= \alpha^{-1}\mathbf{A}\mathbf{L}^T\mathbf{L}\mathbf{A}^T + \beta^{-1}\mathbf{I}_{N_c} \\ \bar{\mathbf{s}}_t &= \alpha^{-1}\mathbf{A}^T\boldsymbol{\Sigma}_y\mathbf{y}_t. \end{aligned} \quad (3.5)$$

$$(3.6)$$

where \mathbf{L} denotes a spatial coherence matrix, which is taking advantage of the graph Laplacian by using a fixed smoothness parameter.

Handling noise estimation is a crucial part of acquiring reliable source estimates. In [SSP⁺13] (Appendix D) the manner in which eye-related artifacts can corrupt the source estimates for low density EEG caps with unevenly distributed sensors is showed. While in a basic form, the noise is taken as uncorrelated, correlated noise can easily be included in the model, either directly in the equations or indirectly through pre-processing the data prior to the source modeling. Direct modeling of the correlated noise can be achieved by replacing the identity matrix \mathbf{I}_{N_c} with a full noise covariance matrix $\boldsymbol{\Sigma}_{\boldsymbol{\epsilon}}$. Estimation of the noise covariance matrix could be, for example, carried out through calibration sessions prior to actual recordings. By estimating the hyper-parameter β online the inverse solver can model the amount of noise present in the data continuously, a feature especially important for naturalistic recordings where the noise can be expected to be more variable than in the laboratory setting.

Contribution of the thesis

The Smartphone Brain Scanner framework implements important basic and advanced data processing methods—filtering, artifact removal, and source reconstruction. Thanks to a modular design, adding and modifying data processing blocks is possible by creating new C++ classes that integrate directly with the core of the framework; the data handler prepares the data in a format expected by the processing blocks and runs the processing method. Examples of such additional data processing blocks that have been successfully implemented but not yet integrated into the stable branch or described in published papers include the already mentioned PCA-based artifact removal; source reconstruction with structured sparsity solutions¹ implemented by Jair Montoya Martinez, visiting our lab from Carlos III University; spatial filter based on common spatial pattern (CSP); classifier based on linear discriminant analysis (LDA) used for BCI application (described in the offline setting in [SSP⁺13] (Appendix D)). With all the data processing blocks, we can start building quite sophisticated pipelines for real-time data processing on mobile devices, including filtering, blink artifact removal, spatial filtering, and classification for BCI application, which significantly pushes the boundaries of low-cost mobile neuroscience. We have presented such a pipeline (sans artifact removal) at a demo session at NIPS 2011 conference [SSL⁺11].

The Smartphone Brain Scanners offers a testbed for experimenting with new data processing solutions in a computationally constrained environment and in the novel context of portable and mobile EEG. As this context is so different from what has been classically considered in neuroscience, some of the solutions may be not obvious, such as the performance of real-time PCA-based blink removal comparable to the ICA-based one. Similarly, we showed that source reconstruction can be feasibly realized on mobile devices with the real-time solver for the ill-posed inverse problem with online Bayesian optimization of hyper-parameters (noise level and regularization) [SSL⁺14] (Appendix F). It is important to note that the Bayesian formulation allows adaptation of hyper-parameters to different noise environments in real-time, rather than applying heuristics for the estimation of the values, as previously done in the real-time source reconstruction [CLL06, NKM08, BMG11]. We also reported performance of the source reconstruction on the mobile devices, using a 1028-vertices brain model (coarse resolution); performing calculations on 1s of raw EEG signal on a Nexus 7 tablet. The reconstruction took 8ms and the update of hyper-parameters took 1s. This shows that it is possible to run source reconstruction with Bayesian formulation on mobile devices several times a second, and to update the hyper-parameters several times a minute. In [SAS⁺12] (Appendix G) we compared how low- and

¹https://github.com/SmartphoneBrainScanner/smartphonebrainscanner2-core/tree/master/src/source_reconstruction/sparse

high-density EEG setups depend on correct forward modeling and examined how chosen forward models affect the source estimates obtained using four inverse solvers: Minimum-Norm, LORETA, Minimum-Variance Adaptive Beamformer, Sparse Bayesian Learning. We showed that even with systems of low-resolution (such as Emotiv EEG or Easycap), it is possible to recover sources located in the temporal lobe reliably for most of the forward models; Sparse Bayesian Learning was proved to produce the most consistent source estimates for the the different forward models.

In [PSS⁺11] (Appendix E) we demonstrated the ability to distinguish among emotional responses reflected in different scalp potentials when viewing pleasant and unpleasant pictures compared to neutral content. The reconstruction of the neural sources (here conducted offline, using Minimum-Norm), facilitated differentiation of these emotional responses. Consistent with earlier neuroimaging findings, the reconstructed sources reflected increased activity in the 150-200ms time window for pleasant versus unpleasant, whereas the pleasant versus neutral content appeared less significant. The 3D reconstruction of the underlying neural sources may not only add to the differentiation of emotional responses captured in a mobile EEG setting, but may also provide an intuitive interface for interacting with a 3D rendered model of brain activity as a basis for developing novel and more natural biofeedback applications. Similarly, source reconstruction was used in [SSP⁺13] (Appendix D) and [SSL⁺14] (Appendix F) for the realization of a Brain-Computer Interface by classifying left/right imagined finger tapping.

Based on the Smartphone Brain Scanner, several student projects in signal processing domain have been successfully realized, notably the Bachelor's thesis of Simon Bøge Henmmingsen *Motor Cortex Control of Smartphone Apps using Neuroimaging*, the Master's thesis of Marieta Georgieva Ivanova *Controlling brainwaves for mobile neurofeedback*, and the Master's thesis of Simon Kamronn & Andreas Trier Poulsen *Machine Learning for Social EEG—A Bayesian approach to correlated component analysis and recording simultaneous multiple subject EEG*.

3.3 Applications

EEG signal captured and processed in naturalistic settings can be used for a variety of applications. Some of them known from classical neuroscience, while others are more specific to the new context. In this section three possible applications of naturalistic EEG are described: Brain-Computer Interfaces (BCI), decoding of emotional states, and neurofeedback.

3.3.1 Brain-Computer Interfaces

One of the most widely used paradigms for building Brain-Computer Interfaces (BCI) is a task in which a subject selects between two or more different imagined movements [MGPF99, BCL⁺00, DBCM04, BDK⁺06]. Such mental imagery is the basis for many BCI systems, originally created for patients with severe disabilities to allow communication by ‘thought’, as an explicit interaction technique [QHMST13]. While patients may have problems carrying out actual movements they may still be able to plan them, thereby producing a stable motor-related brain activity useful as an input for the machine. BCI can also be combined with cognitive monitoring, collecting information about the users’ intentions, emotional states, and situational interpretations, to make up a passive BCI [ZK11]. Designing BCI for able-bodied users presents a set of specific requirements and demands and has so far resulted in implementations of mixed usefulness, primarily due to relatively low bitrates achieved when decoding the brain signal directly. Comparison of several BCI studies, presented in [KVP05], showed the average bitrate achieved was around 11 bits/minute, with the top studies achieving 27-38 bits/minute. Such bitrates can be life-changing for patients not able to use regular input technologies. The able-bodied users, however, produce on average 35-40 words per minute (WPM) when typing on a regular computer keyboard (measured with every word standardized to be 5 characters long) [KHHK99]. Assuming only the English alphabet of 26 characters is used, this results in 5 bits per character and effective bitrates of up to 1000 bits/minute. For this reason a classical BCI application of imagined finger tapping is described as a validation of the system—**hello world** of brain decoding—but the biggest promise of mobile brain imaging systems is expected to come from the applications described later: emotions sensing (passive BCI) and neurofeedback.

When persons think about moving their limbs—even if they cannot actually perform the movement—they produce stable motor-related brain signals: readiness potential (RP) and event-related desynchronization (ERD). The readiness potential is a transient postsynaptic response of the main pyramidal peri-central neurons, leading to negativity in the EEG during motor preparation and peak during movement onset, a process first reported in 1965 by Kornhuber and Deecke [KD65]. When hand movement is considered, the negativity is focused contralateral to the performing hand [CHLD99]. In the event-related desynchronization, the preparation for the movement is visible as an attenuation of mu rhythm (around 8-14 Hz) in the corresponding motor areas. This attenuation is visible bilaterally, but more pronounced contralateral to the performing hand [PLdS99]. The imagined movement produces a less pronounced effect than movement actually executed, yet can still be used for an input.

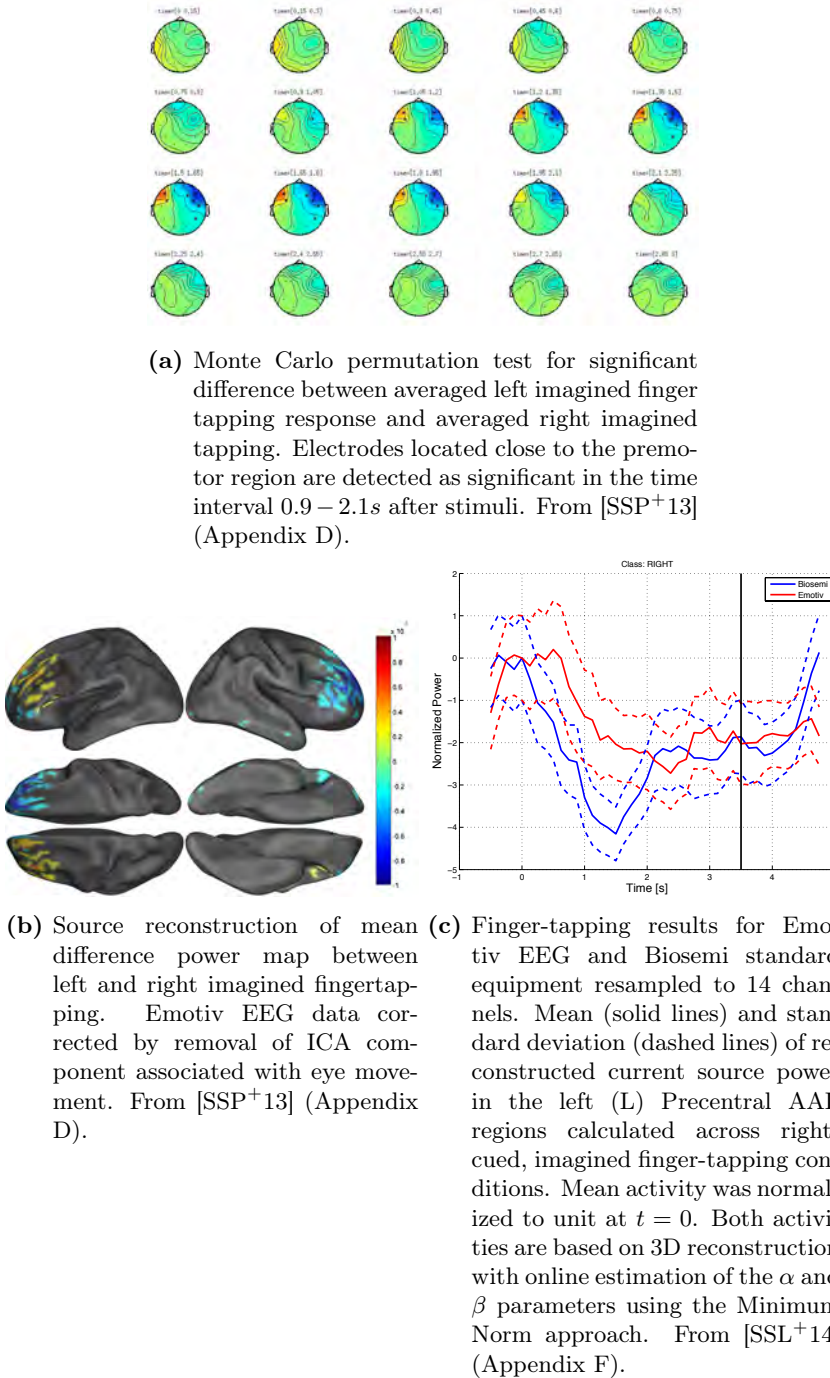


Figure 3.7: Results from imagined finger tapping experiments (left vs. right) inspired by [BDK⁺06], with data collected using both the software and hardware of the Smartphone Brain Scanner.

In [SSP⁺13] (Appendix D) and in [SSL⁺14] (Appendix F) we showed results from imagined finger tapping experiments (left vs. right) inspired by [BDK⁺06], but with data collected using both the software and hardware of the Smartphone Brain Scanner. Figure 3.7 depicts the results from these experiments, showing the nature of the event-related desynchronization. Figure 3.7a shows the time evolution of the ICA components before, during, and shortly after the stimulus by visualizing the difference between averaged left and right imagined tapping and highlighting significant electrodes. As the recordings were performed using Emotiv EEG, which does not contain electrodes directly over the motor cortex, the identified active regions appear slightly to the front compared to their anatomical and expected position. Still, the laterality and timing of the activations indicate a clear ERD signal. Figure 3.7b shows the source reconstruction of the mean difference power map between left and right tapping after ICA-based artifact rejection. We can note the same strongly pronounced difference between left and right hemispheres, with the sources again shifted to the front due to a very suboptimal placement of the Emotiv EEG electrodes. Finally, Figure 3.7c shows the comparison between Emotiv EEG and Biosemi standard (stationary) EEG equipment resampled to 14 channels. Mean (solid lines) and standard deviation (dashed lines) of reconstructed current source power in the left (L) Precentral AAL regions were calculated across right-cued, imagined finger-tapping conditions, with mean activity normalized to unit at $t = 0$. Both activities are based on source reconstruction (Minimum Norm) with online estimation of the α and β parameters and show a clear suppression of the source power, which is expected in the Precentral Left AAL region during imagined right finger tapping.

As an initial validation of the framework, all the analysis described here has been performed offline. The data was collected with a set of three instructions, *Relax*, *Left*, and *Right*, displayed to the participants directly on the screen of a mobile device. The duration of the *Relax* task was randomized (1.75-2.25 s) to minimize the effect of the subject anticipating and starting the task prior to the instruction.

3.3.2 Cognitive & Emotional State Decoding

One of the biggest opportunities presented by development of mobile low-cost EEG systems is the chance to monitor users' cognitive and emotional states in naturalistic settings. Rather than utilizing such systems for active BCI with very limited bandwidth, we can start sensing latent states of the users as they go through their lives. The concept of using mobile EEG systems for passive BCI is presented, exemplified by decoding the cognitive and emotional states of the user.

Neuroimaging studies have established language is grounded in sensorimotor areas of the brain, with the same or similar circuits involved in both motor actions and abstract language expression involving movement [PF10]. Moseley et al. in [MCH⁺11] used action verbs related to emotional expressions and face and hand motion presented to participants while recording brain activity with fMRI in order to test if emotion word-evoked activity emerges in motor brain systems controlling the face and arms. In [SSP⁺13] (Appendix D) we used the same set of verbs in a single subject pilot experiment, comparing the feasibility of distinguishing between such verbs using Emotiv and Easycap EEG hardware setups. Every verb was displayed for 1s on the mobile device screen and the recorded data were epoched and cleaned by removing noisy epochs and artifacts. As the Emotiv and Easycap EEG hardware feature different electrode positions, ICA was applied to linearly project the EEG data from individual electrodes onto a space of independent vectors, creating the scalp maps and time series of neural sources [DSM07]. Retrieving these ICA components enabled us to identify similar independent sources within trials. To identify common patterns of brain activity both within and across the Emotiv and Easycap experiments, we clustered the $2 \times 10 \times 14 = 280$ ICs based on scalp maps, power spectra, and amplitude times series. After artifact rejection in each trial, the dimensionality of the feature space was reduced to $N = 10$ by applying PCA principal component analysis [Jol02], compressing the multivariate EEG features into a smaller number of mutually uncorrelated scalp projections. A vector for each component was then computed to define normalized distances in a subspace representing the largest covariances in the ICA-weighted data. These vectors contained the 10 highest PCA components for the ICA-weighted time series responses, scalp maps, and power, related to the three conditions of face and hand motion verbs and emotional expressions. Clustering of common ICA components within the 10 trials was done with K-means ($K = 10$). With functionally equivalent groups of ICs, it was then possible to identify recurring neural sources present in multiple sessions and recorded with different EEG setups.

In the Emotiv data 2×18 ICs have been clustered in 10 out of 10 trials, showing common activations across all trials, as depicted in Figure 3.8a. Similarly, with Easycap, 23 ICs have been clustered within 3 standard deviations of the K-means centroids in 10 out of 10 trials and 9 ICs have been grouped in 7 out of 10 trials, recovering temporally independent activations grouped across trials in this study, as shown in Figure 3.8b. In both studies, the clustered scalp maps suggest left lateralized prefrontal as well as parietal activations in language areas, responsible for integrating motor and semantic aspects in the brain [RST11, AKP12]. The results agree with these obtained in the aforementioned fMRI experiment [MCH⁺11], indicating that premotor neural circuits are activated when both reading verbs related to face/hand motion and when seeing emotional expressions.

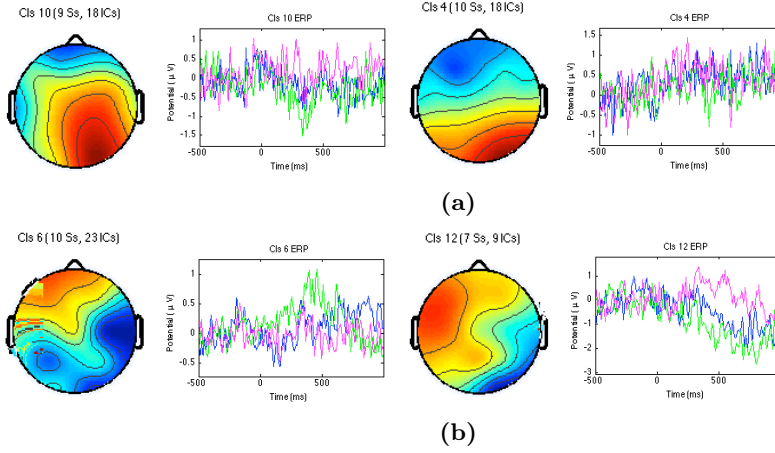


Figure 3.8: Single-subject EEG neuroimaging study with **a)** Emotiv and **b)** Easycap 14 channel EEG setup: PCA dimensionality reduction and K-means clustering ($K = 10$, $\sigma = 3$) of 140 IC scalp maps, activation time series, and event-related changes in power spectra based on 10 trials, each consisting of reading 3×20 emotion (blue), face (green) and hand (pink) related action verbs. From [SSP⁺13] (Appendix D).

Affective terms can generally be represented as related components in a circumplex model described by the two psychological primitives: valence and arousal [Rus80]. It has been established that emotional content, such as pictures, triggers not only automatic responses such as increased heart rate or galvanic skin response, but can also be identified in brain activity with identifiable differences for pleasant or unpleasant experiences [KBH⁺02]. The event-related potential (ERP) amplitudes have been shown to differ when viewing affective pictures of three categories: pleasant, unpleasant, neutral [CSB⁺00]. In [PSS⁺11] (Appendix E), we demonstrated the ability to distinguish between emotional responses reflected in different scalp potentials when viewing pleasant and unpleasant pictures with data collected using the Smartphone Brain Scanner software and hardware. The artifacts were removed using ICA, and activations consistent with previous findings based on high-density EEG setups have been identified in both ICA-based scalp maps and in source reconstructions based on Bayesian formulation of Minimum Norm approach. In the experiment we collected data from eight participants, replicating the setup described in [KBH⁺02] but with a portable EEG system. 3×20 IAPS pictures [LBC⁺05] from the three categories (pleasant: erotic and family photos; unpleasant: mutilated bodies, snakes and spiders; neutral: simple objects as well non-expressive portraits of people) were presented on a smartphone display with 0.5s pre-stimulus of white

cross, 1s presentation, and 1s post-stimulus black screen.

As shown in Figure 3.9, after PCA-based dimensionality reduction, K-means clustering, and artifacts rejection, the ERPs, which were averaged across eight subjects at 300-500ms post-stimuli in 8-12 Hz band, differ across four conditions of pleasant, unpleasant, neutral people, and household objects. We found overall increased posterior activation for pleasant and unpleasant pictures compared to neutral images, as well as increased activation in parietal cortex for pleasant versus unpleasant content. This is consistent with findings reported in [KBH⁺02] and [SJWH04], where activations in central, temporal, and parietal cortex differentiated responses when viewing affective pictures compared to neutral content. The ability to continuously capture such patterns may offer completely new opportunities for modeling the cognitive and emotional state of users in real life scenarios as well as providing a basis for novel biofeedback applications, thereby fully realizing the concept of passive BCI.

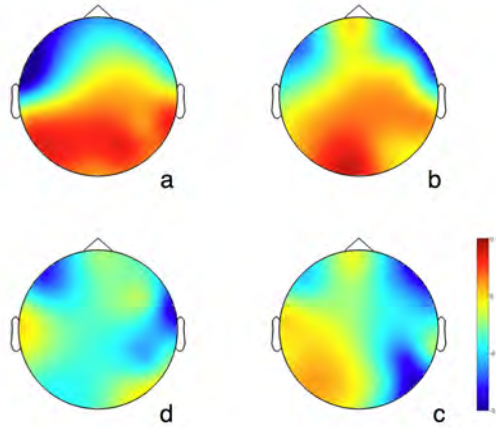


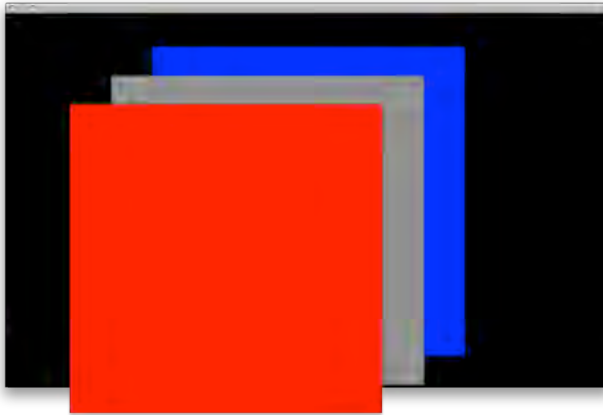
Figure 3.9: Mobile EEG event related potentials ERP averaged across eight subjects at 300-500ms after stimuli in the 8-12 Hz frequency band, depicting: a) pleasant - erotic couples b) unpleasant - mutilated bodies c) neutral people d) household objects. We can note overall increased posterior activation for a) pleasant and b) unpleasant compared to c) neutral people and d) objects, as well as increased activation in parietal cortex for a) pleasant versus b) unpleasant content. From [PSS⁺11] (Appendix E).

3.3.3 Neurofeedback

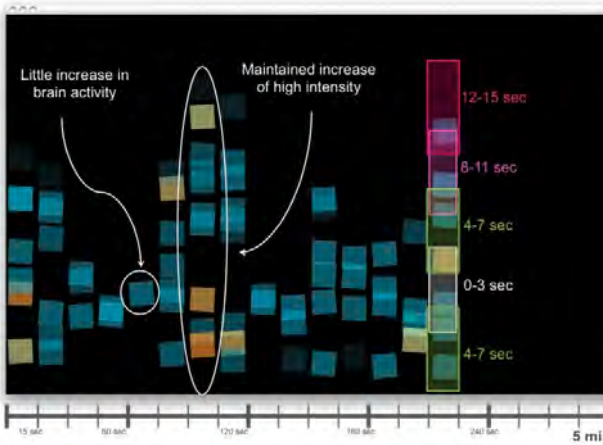
Neurofeedback is a brain-related mode of biofeedback, a technique of gaining control over physiological functions by focusing on feedback information provided by software or hardware systems. For example, neurofeedback experiments to increase the power of the upper alpha band have been shown to improve cognitive performance [HSD⁺05, ZHH11]. An ability to consciously control this band, which appears to be involved in selective attention as a gating mechanism [FS11], might potentially explain the reported training effects on cognitive performance. A correlation between this band and good memory performance has also been reported [Kli99]. Neurofeedback interfaces are, however, classically designed with little attention to how the audiovisual elements may affect the user's ability to control brain activity. While User Experience (UX) development normally involves modeling of the user needs and selection of design patterns for content organization and navigation, development of neurofeedback applications has so far primarily focused on mapping EEG directly onto audiovisual components, such as sounds of ocean waves or high- or low-pitched gongs [EZG04, HNP⁺04] and vertical scales and squares of changing colors [NKK⁺03, VEC⁺03, ZHH11]. More complex environments have been developed for applications for children, such as airplanes, car racing, or a pole-vaulting mouse [GHA⁺09, HGS07]. Still, there seems to be a surprisingly little dialog between UX and neurofeedback communities. Interfaces are developed as a minimal viable product, rather than through an iterative scientific process.

In [SSP⁺13] (Appendix D) we explored the influence of the interface design on the efficacy of neurofeedback training, by testing two interfaces—developed for the Smartphone Brain Scanner—on 25 participants attempting to increase their upper alpha band power. The first interface, replicated from a study by Zoefel et al. [ZHH11], consisted of a color gradient framed by a square, which indicated brain activity below or above baseline, as shown in Figure 3.10a. In the second iteration, we developed an interface combining four components: scaled down color gradients, square primitives, horizontal spatial distribution, vertical spatial distribution, depicted in Figure 3.10b. In the experiments, both iterations included five sessions during a single week (Monday - Friday), with each session starting and ending with a 5-minute baseline recording. The recordings were performed with Emotiv EEG. Real-time feedback was constructed from O1 and O2 channels; the recordings were later re-referenced from P3/P4 to AF3/AF4 and F3/F4 in order to include P3 & P4—positioned in the area relevant for the paradigm—in the offline analysis.

The upper alpha frequency was determined for each participant, to compensate for variability caused by age, neurological diseases, and inherent physiological differences [Kli99]. We identified the individual alpha peak (IAF) in



(a)



(b)

Figure 3.10: **a)** First version of the feedback interface with brain activity visualized by the square changing colors; blue indicating activity below, gray - equal to, red - above baseline. **b)** Second iteration of the neurofeedback application, with additional illustrations describing how it is constructed; the 5-minute timeline shown in the bottom illustrates how the training session is divided into columns of 15 seconds. Within a column squares would appear first (0-3s) in a window in the lower part of the screen, then (4-7s) in windows above and below the first window and lastly (8-11s and 12-15s) in windows above the first two windows. The encircled column illustrates how the user can easily compare the ability to increase brain activity in different time intervals. From [SSP⁺13] (Appendix D).

the first baseline recording of every session, and the upper alpha (UA) frequency was set as a band from IAF to IAF+2 Hz. The participants identified as non-responders—unable to significantly change amplitudes of their brain frequencies—have been removed (3 participants from both the first and second iterations), a practice commonly used in neurofeedback studies [FBL⁺03, GHA⁺09, LSS095, ZHH11]. The EEG results from the baseline and training recordings were normalized to the baseline from the Monday session, thus showing participants' ability to increase UA amplitudes, as plotted in Figure 3.11. We can observe a large variability in the participants' performance; some subjects were capable of increasing their UA amplitudes above 400%, whereas others experienced smaller changes or even a decrease (usually the non-responders). The participants with the highest increase were mainly from the second iteration of the feedback interface, the variance of the performance was, however, also greater in these sessions.

To analyze the impact of the interface on the participants' performance, we fitted regression lines to the individual UA amplitudes as a function of session number (1-35), finding they were significantly greater than zero in both iterations. No significant effect between the iterations was found (tested with a two-sample, two-sided *t*-test), indicating similar effectiveness of both interfaces. To isolate the training effect from the feedback effect (an immediate increase in UA amplitude during session), we calculated the difference between UA amplitude during the first baseline recording in the first session and the first baseline recording in the last session, finding a significant effect in the first but not in the second iteration, which indicates the interface used in the first iteration was more effective for neurofeedback training. The interface used in the second iteration was, on the other hand, more effective for inducing an immediate increase in the UA amplitude, as quantified by a repeated-measures ANOVA with session number as within subject factor and iteration as between groups factor. With no effect of the session number, we averaged the feedback effect across session number and subjects within an iteration and found the mean feedback effect was 0.17 for the first iteration and 0.67 for the second iteration. These results suggest that the immediate increase of the UA amplitude during feedback sessions does not determine the training effect, a possibly important factor when creating neurofeedback applications.

Contribution of the thesis

With low-cost mobile neuroheadsets and advanced software frameworks, such as the Smartphone Brain Scanner, exciting neuroscience applications can be created, including Brain-Computer Interfaces, cognitive and emotional state

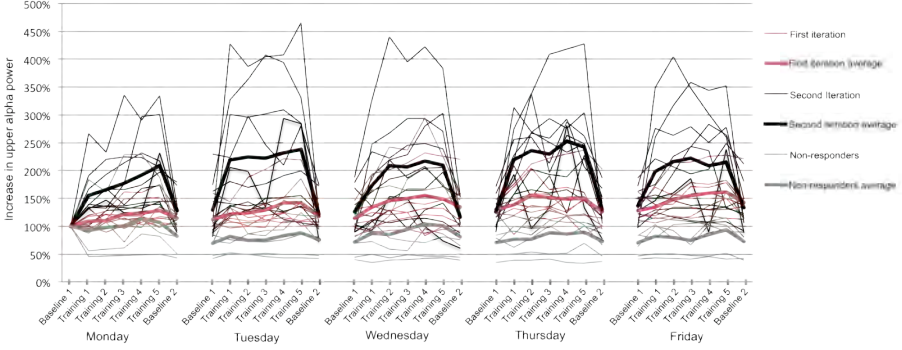


Figure 3.11: The individuals' upper alpha (UA) amplitude in percentage of the UA amplitude from the first baseline recording on the first day (Monday). Subjects from first and second iteration as well as the non-responders from both iterations are plotted in red, black, and gray, respectively. The average of these groups is marked by bold lines in corresponding colors. All baseline- and training recordings have been plotted in sequence across the week, e.g. Monday showing results from the first baseline, then the 5 training recording, ending with the second baseline, giving a total of 7 points of each day. The results illustrate a large variance in the individual subjects ability to increase UA amplitudes, where subjects from the second iteration were capable of reaching a greater increase, although some subjects were unable to achieve any increase at all (referred to as non-responders). From [SSP⁺13] (Appendix D).

decoding, and neurofeedback techniques. In the contributions described in this section we have shown the validation of the developed software and hardware with respect to more- and less-known paradigms: BCI-based finger tapping in [SSP⁺13] (Appendix D) and in [SSL⁺14] (Appendix F); emotional and cognitive state decoding in [SSP⁺13] (Appendix D) and in [PSS⁺11] (Appendix E); and neurofeedback interface validation in [SSP⁺13] (Appendix D).

For the BCI application, we reported results of a cued, imagined finger-tapping experiment. With offline analysis, we showed the evolution of independent components during the task, source reconstruction of the brain areas, and comparison with conventional state-of-the-art laboratory equipment with respect to activations in relevant reconstructed motor areas. We found that these signals compare favorably with those obtained with standard equipment, showing the expected significant de-synchronization on initiation of imagined motor actions. This way, we have performed a thorough laboratory validation of the developed

low-cost mobile software and hardware. The validation stands firm in respect to the difficult challenge of synchronization between recorded EEG signal and system events—stimuli presentation and user responses. We have presented a real-time BCI setup of the Smartphone Brain Scanner at NIPS 2011 conference [SSL⁺11], classifying imagined finger tapping with CSP and LDA on the sensor level. Combining sensor and source features has been shown to improve classification in BCI [AHJ12], even though these paradigms often involve activation of sensorimotor circuits where the location of the sources is already well known, an important and—as our results indicate—feasible opportunity for increasing the classification rate in a noisier mobile signal.

For the cognitive and emotional state decoding, we were able to show the potential of a low-cost EEG system for naturalistic sensing of the latent states of the user. Replicating and extending exciting studies [KBH⁺02, SJWH04], we demonstrated how responses differ between pleasant and unpleasant content, with overall increased posterior activation for pleasant and unpleasant compared to neutral, as well as increased activation in parietal cortex for pleasant versus unpleasant content. Consistent results were obtained in activations from sources reconstructed with Bayesian formulation of Minimum Norm approach. We were also able to obtain results agreeing with those reported by Moseley et al. in [MCH⁺11] regarding the activation of premotor neural circuits when passively reading verbs related to face and hand motion and when seeing emotional expressions. Although those results are from a preliminary study, it is significant that a low-cost portable EEG system can be used as a brain-imaging setup, producing results in line with those obtained in an fMRI study. Mobile neuroimaging could extend our ability to explore such action-based links between motion and emotion in naturalistic contexts, which might reflect imitation of gestures or facial expressions involving mirror neuron circuits in the brain, and possibly provide a foundation for higher level feelings of empathy and theory of mind.

In the neurofeedback study we confirmed the findings of Zoefel et al. [ZHH11], but again using an inexpensive and more user-friendly setup. Going beyond replication, we tested the impact of the visual interface on the participants' performance, suggesting the ability to control neural activity is very individual and the interfaces should be created to support the individual's strategies. It is an important result, especially when building user-oriented neurofeedback applications for use at home and over extended periods of time. Such context is a new direction for development of neurofeedback applications, where users can not only perform the training in the comfortable environment of their homes and over unprecedented periods of time, but the researchers can collect significant amounts of data regarding day-to-day variability in brain activity and its impact on cognitive and emotional performance. By showing the feasibility of using such a low-cost system and exploring the importance of the visual interface, we took

an important step in the realization of this vision.

Several student projects have explored the potential of building applications on top of the Smartphone Brain Scanner, including the Bachelor's theses of Michael Kjellerup & Ibrahim Tareen *Optimization of mobile interface design for neurofeedback training*, Benjamin Dalsgaard Hughes *Design of a smartphone app for brain machine interaction*, Martin Hastrup *P300 brain machine interface for mobile neurofeedback*, and Anders Sørensen *Design of mobile interfaces for neurofeedback training* and the Master's thesis of Camilla Birgitte Falk Jensen *Using mobile interfaces for neurofeedback training*, whose work was later extended and presented in the papers.

CHAPTER 4

Privacy of Personal Data

As our sensing capabilities are growing, we collect data about larger populations, over long periods, and from continually advancing sensors. Inherently, some of these data or compositions thereof are sensitive; they are private in a sense that individuals should be able to control who has access to them. This creates new challenges, both within and beyond research studies, including privacy-aware data sharing and user consent.

This chapter outlines the challenges in ethical, responsible, and efficient treatment of personal data. Section 4.1 outlines the concept of a Personal Data System, a framework for privacy-preserving data sharing developed and implemented at MIT Media Lab and at DTU. Section 4.2 focuses on methods of empowering the user to express informed consent to data collection, sharing, and analysis.

4.1 Personal Data System

Researchers, companies, and governmental institutions collect increasingly more sensitive data about all aspects of human lives. These data include mobility traces, social networks, medical and health-related records, psychological traits, and financial transactions, to name just the most common ones. These rich datasets offer a great opportunity for understanding societies and for creating systems reacting to people's needs in an adaptive way, as outlined in [GSS⁺14] (Appendix A). For this vision to become reality the data must be available when needed, primarily in an aggregated form useful for understanding society-scale process. At the same time, a successful data-driven society must be able to guarantee that personal data will not be abused. Abused, for example, by imposing higher insurance rates based on shopping history [Git13] or by harming the entire society by limiting user choices and enclosing them in information bubbles [HSMK⁺13]. Sharing raw data with for-profit services or even researchers may be problematic, primarily for two reasons: very many things can be inferred from high-dimensionality data, today and in the future, and it is hard for users to comprehend how sharing such data affects their privacy and what value they should expect in return. On a practical side, sharing and moving such huge raw data is becoming increasingly impractical in the research context, with hundreds of gigabytes of data generated by users in deployments such as the Copenhagen Networks Study that have to be accessed and analyzed by many researchers. Sending the datasets as csv files for local analysis is not feasible in such a scenario.

To overcome the problems with privacy concerns around sharing high-dimensional data, I have been involved with a group at MIT Media Lab, developing and testing open Personal Data Store¹ (openPDS), an architecture for sharing high-level extracted features in the form of answers from personal data, rather than data themselves [dMWP12]. Such a method of data sharing is a critical step in the technical improvement of data ownership. As valuable knowledge can be inferred from data coming from multiple sources—for instance, fitness data matched with psychological profile, combined with day-to-day mood and activity on Twitter—the only reasonable focal point of data ownership are users themselves, as outlined in the vision of the New Deal on Data [Pen09]. By sharing answers, rather than raw data, the privacy of users can be significantly improved, by making it easier for them to understand how the data will be used and by inherently decreasing the possibility of unauthorized uses of such extracted features. For example, rather than sharing a raw GPS trace, the user can decide to give access only to her city to a music service in order to get a personalized music station. Extraction of the features—based on all available raw

¹<http://openpds.media.mit.edu/>

data but in the domain controlled by the user—is an important step towards fair information practices, in which the value of the data can be better understood and used. Large Internet services have quite recently started implementing sensitivity reduction when exposing data to third parties. For example, Facebook introduced a scope `age_range` allowing user to authorize applications to only access whether the users’ age is in the range [13-17, 18-20, 21+] rather than the exact birthday, as shown in Figure 4.1. This way, applications can use information from Facebook to allow age-based access for the users, without learning the exact value, which could be misused, e.g., for targeted advertising.

Fields

| Name | Description | Type |
|-----------|--|--------------------|
| id | The id of this person's user account. | numeric string |
| age_range | Unspecific age range that this person's age fits into. | object |
| min | The lower bounds of the range for this person's age. | enum{13, 18, 21} |
| max | The upper bounds of the range for this person's age. | enum{17, 20, None} |

Figure 4.1: Facebook implementation of an OAuth2 scope reducing sensitivity of disclosed information. Rather than providing the exact birth date, users can authorize applications to access only age-range, information sufficient for most cases of age-controlled access. From <https://developers.facebook.com/docs/graph-api/reference/user>.

In [GSS⁺14] (Appendix A) we outlined the impact of openPDS architecture on how research can be conducted and on how society can be governed. Building on experiences with large-scale data collection and with personal brain imaging in [SGHP14] (Appendix I), we described how openPDS architecture can be utilized in the context of personal neuroinformatics. Identifying the sensitivity of EEG signal, obtained with even low-dimensionality systems, we postulated that raw EEG data should remain under user control as much as possible, with only high-level features shared with the services. The outline of the architecture is depicted in Figure 4.2 and corresponds to a generic openPDS architecture. Raw EEG data are recorded by the user, uploaded to the server, and stored in a database. By having all the data available, potentially combined with additional channels of personal data such as mobility traces of Twitter activity, it is then possible to perform various computations, producing high-level features. These features are calculated in the background and stored in the database, so they

can be readily available when requested. This architecture benefits from the fact that in the context of creating insights, most often the applications do not require strictly consistent data i.e. the answers might be minutes, hours, or even days old and still valuable. This way, the dimensionality reduction, the computationally heavy process in the system, can be performed continuously and on the best-effort basis, fully utilizing the available resources, while at the same time quickly serving relatively small pre-computed answers for the applications. The methods for calculating those features can be provided by the services, with the code approved to operate in an expected manner. PDSes can also engage in group computations, providing answers about groups of users, both increasing privacy and making the answers potentially more valuable, describing larger populations.

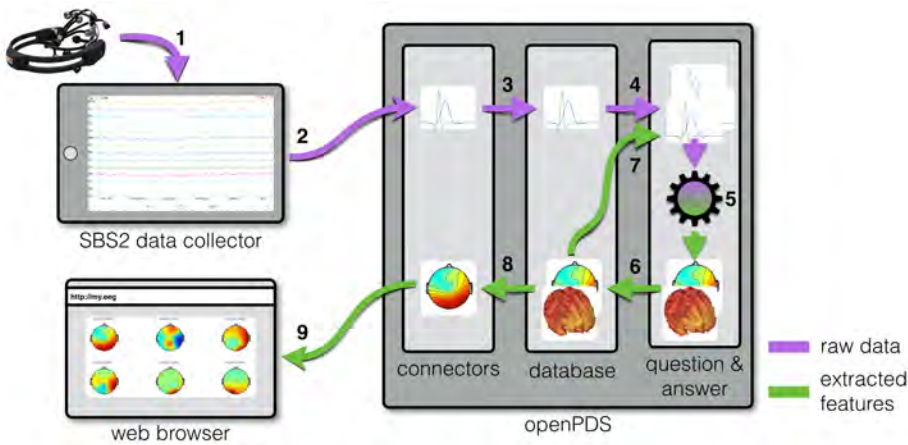


Figure 4.2: openPDS architecture, used in personal neuroinformatics context. Raw EEG data are collected from a neuroheadset on a mobile or stationary device (1) and uploaded to a server as a binary file (2). Data are then extracted and populated to a database (3). Periodic question & answer computation process operates on the raw data (4) extracting the high-level features of the data (5). The features are populated into the database in a form of high-level answers (6). Those answers can be used for the computation of other features (7). The pre-computed answers are accessed from the database (8) and served to the requesting application (9). From [SGHP14] (Appendix I).

Development of Personal Data Stores is an important step towards creating data portability, allowing for the transfer of the data between services, governmental institutions, and research studies, which is one of the big challenges in the

current state-of-the-art of data handling. It can be seen as building vessels of personal data, traveling with users across space and time. We are convinced that there is amazing potential in using personal data to learn about and to react to the needs of societies. OpenPDS architecture achieves it by putting the user in control, thus making it feasible to collect and combine data from many different sources, which is especially important when modeling complex social systems [SSS⁺14] (Appendix B). To protect the privacy of the users, the raw data is not shared, but the computations run in the user-controlled domain. This simplifies the picture of the data flows between the services and how the users can own, manage, and control their data.

Contribution of the thesis

In [GSS⁺14] (Appendix A) we outlined how the Personal Data Stores fit into the new economy of personal data. Following the ideas from the New Deal on Data, we described the business, legal, and technical dimensions of incorporating end-user data ownership in different contexts, postulating that the technical solution of user-owned multi-source data store is one of the requirements for a successful transition to data-driven science and economy. Significantly, we described how moving the control point from the data collection to data sharing—simply assuming that all possible data is somehow being collected—can simplify the architecture of the systems and enhance the user privacy by providing more effective control.

In [SSS⁺14] (Appendix B) we described our implementation of openPDS in a large sensor-driven human data collection efforts, the Copenhagen Networks Study. Within the study we are not only collecting the data and experimenting with social structure, but also testing new privacy solutions, including the development of openPDS and its question/answer framework. We significantly developed the privacy system, including question/answer framework, authorizations, identity provider, and advanced in/out connectors in a 3-layered architecture of platform, services, and application, thereby creating a Personal Data *System*. In [SPP⁺14] (Appendix H) we reviewed important practices in the collection of massive sensor-driven data and components of Personal Data Systems, including security solutions, data storage, and user authorizations. In [SGHP14] (Appendix I) we showed why EEG data should be considered sensitive and thus be treated as personal data from business, legal, and technical viewpoints—finding in the process that surprisingly little attention has been paid to this issue so far. Brain recordings should live under user control in a PDS, leaving it as little as possible, with high-level answers—possibly computed by mashing with other data sources—being shared instead. Thus, we proposed an integra-

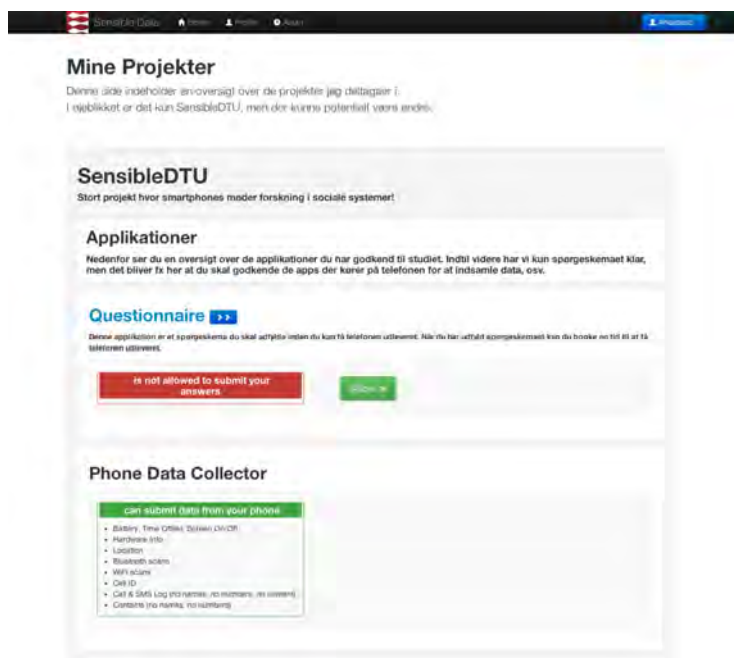
tion of a personal neuroinformatics system, the Smartphone Brain Scanner, with a general privacy framework—openPDS.

Several student projects have been exploring the extension of the Copenhagen openPDS, including special project by Magdalena Furman *Questions and Answers Framework for Quality Control of Massive Data Sets* and Master’s thesis of Riccardo Pietri *Privacy in Computational Social Science* (based on which [SPP⁺14] (Appendix H) has been later developed) and Luis Fernando Flores Vargas *Mining spatial knowledge from large scale deployment of distributed mobile sensors*.

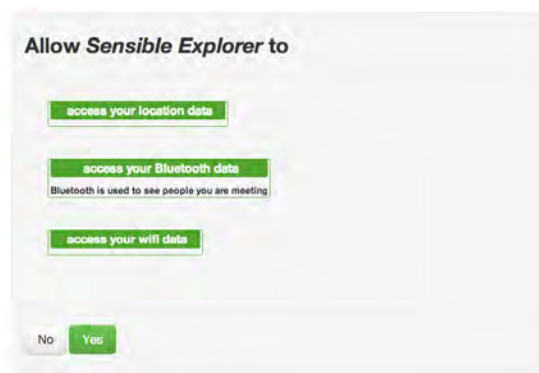
4.2 Living Informed Consent

Business, legal, and technical solutions to the challenges of data ownership are only effective if the user can exercise control in an informed way. In academic studies, this control is called informed consent and consists of an agreement between researchers and participants about data collection, transmission, storing, sharing, and analysis. The users should be able to comprehend which information is collected, how it is accessed, what the incentives are, and what the purpose of the study is [FLM05]. Ethical behavior of the researchers plays a central role in protection of the participants, supported by legal framework of agreements about allowed and disallowed use of the data. The procedure of informed consent has been introduced in the Nuremberg Code, after the discovery of torture practices performed as ‘research’ by Nazi doctors [U⁺92]. It is now considered a cornerstone of the subjects’ rights, imposing legal obligations on the researchers with respect to the nature of the relationship, proper information procedures, or right to refuse participation in research [BALP01].

Most of the informed consent procedures used today lack granularity in terms of both provided information about what and when is collected and used and what authorizations participants may grant [FGW11]. This is primarily driven by technical challenges, as it is not feasible to contact the user every time the data are accessed, either for information or authorization purposes. It is a general practice that once the consent is granted by the participant, the data contributed to the dataset become a de-facto property of the researchers, who are free to analyze, modify, or redistribute them, typically observing the requirement of basic de-identification. Since so little is understood about what can be inferred from high-resolution data, such everlasting datasets without renewed consent can be very challenging in terms of providing proper privacy for the users. To make the issue even more complex, the notion of privacy can be context-specific [TCD⁺10] and vary across cultures and social groups [ABK09].



- (a) User authorizations page . Participants have an overview of which applications are able to submit to and access their data. This is an important step towards users' both understanding what happens with their data and exercising control over it. From [SSS⁺14] (Appendix B).



- (b) Application authorization dialog. Requested scopes are explained in a simple language, with the goal of moving away from accessing the raw data towards accessing high-level extracted features.

Figure 4.3: Data collection system from the Copenhagen Networks Study with the authorization screens presented. An early implementation of Living Informed Consent, empowering user to understand and to exercise control over data sharing.

Presenting extensive information about a study does not guarantee a truly informed consent, as participants tend to trust the validity of the default settings and accept any conditions which they perceive as authoritative [BK10] or may not comprehend the complex language presented to them [CZSSM80, POTB03, SMP⁺99]. Studies of how to improve this situation have been conducted in ongoing clinical trials [LSHF99] and through feedback sessions regarding the consent procedure [KBD⁺10, MKHS08]. One of the possible solutions—granting permissions gradually over time—has been discussed as having both positive and negative impacts, as breaking down the consent may facilitate understanding [EFW12] but may become distracting to the user [KHFK07]. Multimedia augmentation of the informed consent, on the other hand, can improve participants’ understanding of the study design, most significantly in mentally ill patients [DLP⁺02, ACG⁺03] but not necessarily in the general population [FMM⁺97, WHD97].

We believe that user-ownership of data is an important advancement in how data can be collected, accessed, and used, as outlined in the PDS section. At the same time, increasing the granularity of control and number of decisions for the user to make may effectively work against users’ privacy—teaching them to agree to everything—or may cause the opposite no-to-everything behavior, burying the data forever. It is important that consent procedures and implementations evolve side-by-side with increased data ownership, making this control meaningful. For this reason, in [SPP⁺14] (Appendix H), we proposed the term *Living Informed Consent* for aligned business, legal, and technical solutions empowering participants to understand the type and quality of the data collected, not only during the enrollment, but also as the data is being collected, analyzed, and shared with third parties. For this to become reality, informed consent must be implemented as a core part of the data collection system so that the user can stay in touch with the collection process and all the parties involved, rather than expressing consent in a single event only when enrolling into the study. Participants should become users, with a virtual space where they could change their authorizations, drop out from a study, request data deletion, and audit data access. Such an approach is compilable with an ongoing discussion, happening primarily in the biomedical field, about the need for improvements and for more user control in the consent procedures [Sim03, Hay12]. One of the challenges being discussed is how the end-user ownership may impact reproducibility and replicability of the results [Dru09]. This problem is potentially different across domains [Bis13], which may mean it would require additional legal and technical solutions for securing the possibility of revisiting studies and their results.

In [SSS⁺14] (Appendix B) we described the implementation of Living Informed Consent in the Copenhagen Networks Study. The participants’ authorization page is depicted in Figure 4.3a, where the applications can be authorized to submit and access study data. It is an important step in moving beyond lengthy,

incomprehensible legal documents accepted blindly by the users. In the deployed system, the authorizations are still primarily about raw data, making it a challenge for the user to truly comprehend what is really being accessed. Such an authorization request is depicted in Figure 4.3b. However, as we develop the utilization of the openPDS philosophy of sharing answers, rather than the raw data, the authorizations will become increasingly easier to comprehend. Sharing high-level features is not only better for privacy because it limits the possible non-authorized uses of the data, but also because it makes the authorization process easier for the user to comprehend. For example, rather than granting access to Bluetooth data, users would grant access to ‘people you have met since Wednesday’. This emphasizes the idea that the most valuable point of control is data sharing rather than collection; what is really important is answers extracted from the raw data, not the data themselves.

Living Informed Consent is primarily useful for the data accessed frequently and in real-time: mobility patterns, fitness, social activity. As research studies, such as the Copenhagen Networks Study, move beyond frozen, aging datasets and utilize fresh data for both research purposes and building applications, participants must be given more powerful tools to understand gains and consequences of data sharing. With the growing size of the studies, explaining the goals and procedures in detail and in person to every participant becomes infeasible; thus the need for solutions simplifying the consent procedure, without trivializing it. Living Informed Consent implementations, backed up by openPDS question/answer framework can be a feasible solution for addressing the rising problems of consent procedure.

Contribution of the thesis

Development of advanced informed consent procedures, together with associated data ownership and research access practices, will play a crucial part in the journey towards larger and more sophisticated sensor-driven human data collection efforts. In [SPP⁺14] (Appendix H) we proposed the term Living Informed Consent for continuous practices of interaction between researchers and participants for information and authorization purposes. We grounded the discussion about informed consent in the historical and current background, showing that although the idea of improving consent practices is not fundamentally new, recent developments in scale and depth of collected data prompted a new discussion about deficiencies of current consent practices. Whenever data availability is discussed in a research context, reproducibility and replicability of the studies must be considered; in the paper we discussed how greater end-user control may impact them and what the possible measures are to ensure science

may be practiced successfully. We also included privacy-related suggestions for the practitioners of sensor-driven human data collection, including reporting of the informed consent procedures in order to allow building the best practices in the field. In [GSS⁺14] (Appendix A) we put Living Informed Consent into broader perspective, describing business, legal, and technical dimensions of moving towards end-user assent practices, thus defining a comprehensive picture of the new privacy ecosystem. In [SSS⁺14] (Appendix B) we described an early implementation of Living Informed Consent in a research study. It is important to note that in the Copenhagen Networks Study, informed consent practices are not implemented solely to support data collection, but also to enable research on how to improve the privacy of the participants and their understanding of the collected and used data.

Within the framework of Living Informed Consent, the Master's thesis of Albert Fernández entitled *Data Visualization for Informed Consent* is currently in progress.

CHAPTER 5

Future Outlook

The work presented in this thesis is foundational for large-scale sensor-driven human data collection with depth and high-resolution. Both the Smartphone Brain Scanner and the Copenhagen Networks Study projects are only at the beginning of their expected lifetimes, only starting to produce the most exciting results. In this chapter, future work in the domains addressed in this thesis is outlined.

5.1 Large-Scale Sensor Driven Human Data Collection

In [SSS⁺14] (Appendix B) we reported the preliminary results from the Copenhagen Networks Study, showing how multiple streams of data are necessary to more fully understand complex social systems, including human interactions, behavior, and mobility. As the Copenhagen Network Study stabilizes in terms of the number of participants, infrastructure, and data quality, more advanced analysis of the evolution of social systems will be possible. Moreover, with a feedback channel carried by the participants in their pockets—mobile phones—we will be able to deploy experiments and interventions modifying behavior, adding to a well-established baseline from passive observation. In the observational study, we are primarily interested in evolution of social behavior—how the groups form and dissolve and how we can define communities in social networks. We are convinced that with high-resolution multiplex data we will be able to address the challenge of finding and defining communities in a novel, much simpler way. From the experimental perspective, we aim to investigate epidemiological models of spreading in multiplex networks. Within the Copenhagen Networks Study, we have an unprecedented opportunity to observe how (simulated) epidemics change participants' behavior, which in turn changes the spreading pattern. Classically, epidemiological studies focused on how behavior—manifesting as network structure—influences the spreading, but we intuitively understand that when people feel sick they modify their interaction patterns by staying home, not shaking hands, and limiting physical contact. Studying such phenomena in large-scale over long periods of time has been challenging, but with the feedback channel we can simulate epidemics and observe how they spread in a social system when the nodes are aware of the process. Such studies have been conducted, for example, with online games [Bal07], in which the users' avatars could be infected in the epidemic outbreak (accidental or purposeful) and the resulting behavior could be observed. For such experiments to be valuable, a well-established baseline behavior must be known and participants must have a serious incentive to avoid the disease while trying to modify their usual behavior as little as possible, conditions difficult to create in a lab.

The size of the studies, in terms of population, duration, and observed channels will continue to increase. Collection of high-resolution data for studying human behavior will continue to be challenging, even when offset by technical advancements. Technical preparations, administrative tasks, and managing data quality will require reusable solutions and best practices; entire systems allowing for easier deployment, and containing privacy policies, procedures, and data collection, handling, and analysis, will be needed. Studies will increasingly use pre-existing personal data, and the accessing of participants' Facebook, Twitter,

or Fitbit—in addition to data collected specifically within a given study—is a feature that must be considered and supported in the data collection systems. Handing out thousands of phones is not feasible when scaling up the studies, due to expense and management difficulty. The systems will thus have to offer real-time access to the data for building novel applications for the participants to make them interested in joining and to stay engaged. The interest of the participants depends on the value they get in return and the inconvenience the study imposes on their lives. The inconvenience can be measured by decreased battery life of their phones, trouble of answering questionnaires, and giving up some privacy. This has to be offset by the provided value; if not money or material incentives, the value will have to be interesting services built on top of the personal data. At the same time, the systems will have to give more control over data flows to the users, improving how their privacy is handled. This will create new challenges and amplify the existing ones, such as replicability and reproducibility of the results or selection bias in the context of full end-user data control. Systems, such as the one created for the Copenhagen Networks Study and described in this thesis, including Living Informed Consent and openPDS will have to be further developed and standardized.

5.2 Personal Brain Imaging

Future developments in low-cost mobile brain imaging will happen in three domains: hardware, software, experimental paradigms. The hardware used today is only the first iteration of the consumer-grade and research-oriented mobile EEG systems. On one hand, we can expect the high-density systems to become mobile, while aiming for the best possible quality of the signal acquired in naturalistic conditions. Subjects will be able to stand up in the lab and walk around, possibly go outside, or interact socially. The experiments will still be tightly controlled and have a classical researcher-participant relation, but there will be more mobility and degrees of freedom added. In the opposite direction, the consumer-oriented EEG headsets will continue their evolution. Their development will be primarily driven by particular use-cases, and they will become smaller, concealed, and user-friendly sensors including, but not necessarily advertised as, EEG devices. In addition to EEG signal, they may collect other physiological signals, such as EMG, EOG, ECG, and skin conductance. The quality of the obtained signal will be relatively poor, but the devices will become ubiquitous, with a large population owning and using them regularly. Making such data accessible in a privacy-preserving manner and creating analysis methods capable of handling long, low-resolution, and noisy signal will be a challenge requiring a multidisciplinary approach.

By taking EEG out of the laboratory, we will be able to measure the brain activity of a freely moving subject, allowing us to characterize the neural activity associated with many important functions and to study cognitive tasks in their full complexity. Examples include preference-based choice, the updating of working memory throughout the day, or natural social interactions. We have already used the Smartphone Brain Scanner to perform a recording of brain activity of nine people simultaneously watching an emotional video, an experiment hard to realize with expensive, classical EEG systems. Natural environments will allow researchers to characterize the neural function of the perceptual systems when they are embedded in rich multimodal environments, both providing stimuli and receiving input. The complexity and variability of data collected this way will be much greater than when collected in a tightly controlled laboratory setting, potentially requiring huge amounts of data to allow for statistical inference. As mentioned, ubiquitous wearable EEG can provide the solution, with longitudinal recordings collected from large populations, different from lab-based experimentation. For this, real-time applications, possibly operating directly on mobile devices, need to be developed. The Smartphone Brain Scanner, presented in this thesis, is the first framework that enables such development, pushing the limits of what can be done in terms of creating user value by enabling novel EEG applications.

One of the most exciting opportunities offered by mobile EEG is integration with other data sources. Very soon we will integrate brain recordings, obtained with mobile and lab-grade EEG and fMRI, with the data collected in the Copenhagen Networks Study. While the lab-grade systems will be useful for creating a small controlled dataset of brain activity of the highest possible quality, we expect that the flexibility of the Smartphone Brain Scanner will allow us to collect data from larger populations, simultaneously, over extended periods of time, and eventually in fully naturalistic settings. Such data, when combined with all the hitherto collected psychological and behavioral information, will provide an unprecedented opportunity to integrate how we learn about human beings based on their brain activity and their behavior. With concurrent recordings of EEG and behavioral data, the EEG data become grounded, symbolic in nature, and the information content can be much higher than raw bit rate [SvGOH10], a great promise of integrated sensing.

5.3 Privacy of Personal Data

The new data ownership practices have to be supported by the end-user expression of informed consent and resulting orchestration of data processing in business, legal, and technical domains. Within the Living Informed Consent

framework, participants in long-lasting studies with complex data flows will be able to express their preferences and monitor the results of their decisions. Not only will this improve their privacy, but will also be beneficial for the research community by allowing access to greater amounts of pre-existing data from the users, rather than starting every collection anew. Another key aspect of ensuring better privacy has to be contract governance, in which every flow in the system, every data access, is accounted for and can be audited against the authorizations existing in the system at that time. The question/answer framework of openPDS architecture should be used to limit the dangers of sharing high-dimensionality data and to simplify consent procedures for the user. All the mentioned elements—a reusable integrated system, Living Informed Consent, questions/answers—are present in the system developed for the Copenhagen Networks Study. This solution is now actively used as a testbed for developing more advanced privacy mechanisms, including answer-based data flows, robust auditing, and a data access dashboard. As the study expands and involves participants from outside of the university the significance of these solutions will increase. Just as with any other science, robust, efficient, and workable privacy solutions have to be developed iteratively and as a process.

Similarly, existing and new services collecting and processing massive biomedical and health data—including EEG—should adapt the openPDS approach by offering hosting of the user data with the understanding that users can control accesses to the data, request deletion, or move the data to another service provider. Within those services, clear boundaries should be set that would define the business, legal, and technical aspects of what is under user control and what extracted high-level answers can be used for providing the service. Many questions still need be answered in relation to brain activity recordings being viewed as personal data, including applicable legal frameworks, sensitivity of the extracted features, and potential for identification. Understanding these will be crucial for providing privacy for personal EEG data.

On the societal scale, implementation of the end-user data ownership and the New Deal on Data will happen in phases. Firstly, the citizens will have to gain access to the information about what data are collected about them by whom. It is hard to demand ownership if one does not know that the data exist. For this reason, with a team at MIT, we have started an initiative of developing a personal data notice registry—Clear Button¹—where citizens could see the information about their personal data being collected. The next step will be to provide a standardized way of requesting a copy of personal data from multiple research, private, and governmental institutions. Finally, once the users can aggregate their personal data, Living Informed Consent and openPDS frameworks will allow them to decide with whom the data should be shared

¹<http://clearbutton.net/>

and for which purposes. This way we will be able to break the silos of trapped data and make sure it is available when needed for the purpose of research and improving our society.

CHAPTER 6

Conclusions

The work presented in this thesis has addressed the challenges of sensing human beings—their behavior, emotions, and cognitive state—and of using the collected data for understanding human nature. Three domains have been investigated, namely the sensing of large-scale complex social systems, mobile brain imaging and its integration with sensor-driven human data collection, and privacy considering high-resolution sensitive data. In this chapter, the main conclusions are summarized.

Summary

The main focus of this dissertation has been on expanding our capabilities of sensing human beings and the complex social systems they create, primarily using mobile devices. The three main areas of research have been: extending the size of computational social science studies, developing mobile brain imaging system, addressing the privacy of participants.

Sensing complex social systems in a comprehensive way is a challenging task, as multiple channels have to be observed, with high-resolution, on large and densely connected populations, and over long periods. Deploying studies of this kind is a challenge from technical and operational perspectives, but it is extremely important that we learn about the microdynamics of our societies to understand information and disease spread, ties formation, or impact of social structure on our performance. Here, the largest computational social science study to date—the Copenhagen Networks Study—has been described. In a comprehensive overview we outlined the motivation, challenges, and solutions in such large deployments, complete with applied privacy practices and a developed reusable system for data collection and management. The initial results clearly show how crucial it is to observe social systems on multiple channels, as no single channel captures all the important properties of the system. With the Copenhagen Networks Study deployed as a testbed for experimentation, we showed how the self-reported and sensed network of friendships is correlated with group performance and how this relation is strongly non-linear, with only the strongest ties being significant. The inclusion of the network of strong ties rendered measured and self-evaluated technical competencies or personality of the group members non-significant in the statistical analysis. These results have important consequences for the organization of groups of scientists, engineers, or other knowledge workers working on solving complex problems.

Observing the behavior of the participants—their mobility and social interactions—is important for learning about human beings, but it does not provide a complete picture. Recording the brain activity directly—here with Electroencephalography (EEG)—may allow assessment of the emotional and cognitive state of the participants more directly, thus providing an additional channel in integrated human sensing. The Smartphone Brain Scanner described here is an effort to build an extensible advanced data collection and processing framework for low-cost consumer-grade neuroheadsets and mobile devices. Although portable and mobile EEG has been around for some years, it is only recently that the advancements in hardware, software, and our understanding of the brain prompted a call to relax lab conditions and to perform recordings in more naturalistic conditions. Here, we showed how a low-cost portable and mobile system—including custom-built software and hardware—can be used for a variety of applications,

including Brain-Computer Interfaces (BCI), emotional state decoding, and neurofeedback. Using advanced data processing techniques in both online and offline settings, such as artifact rejection, Independent Component Analysis (ICA), or source reconstruction, we showed that although the quality of signal obtained with such setup is lower than with standard lab-grade equipment, it may still be sufficient for a plethora of applications while allowing for more mobility and naturalistic conditions. This will eventually make it possible to integrate brain activity recordings with behavioral data for large populations.

With increasingly sensitive data, including psychological traces, behavior, and brain activity, the privacy of the participants is becoming even more important. Here, we described the open Personal Data System (openPDS), which has a question/answer framework for privacy-preserving data sharing, implemented in the Copenhagen Networks Study. In addition to the technical solution of openPDS—described in a behavioral and a brain activity data context—we postulated Living Informed Consent, a framework for integrated business, legal, and technical approaches to end-user control over data sharing. We extended the vision of openPDS and Living Informed Consent beyond the research context, outlining how personal data ownership can change the way we learn about and govern our societies.

APPENDIX A

Institutional Controls: The New Deal on Data

Daniel Greenwood, **Arkadiusz Stopczynski**, Brian Sweatt, Thomas Hardjono, and Alex Pentland. Institutional Controls: The New Deal on Data (Book Chapter). *Big Data, Privacy, and the Public Good: Frameworks for Engagement*. Edited by Julia Lane, Victoria Stodden, Stefan Bender, and Helen Nissenbaum. Cambridge University Press, 2014. Hardback ISBN 9781107067356; paperback ISBN 9781107637689

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9

The New Deal on Data: A Framework for Institutional Controls

Daniel Greenwood, Arkadiusz Stopczynski, Brian Sweatt, Thomas Hardjono, and Alex Pentland

Introduction

In order to realize the promise of a Big Data society and to reduce the potential risk to individuals, institutions are updating the operational frameworks which govern the business, legal, and technical dimensions of their internal organizations. In this chapter we outline ways to support the emergence of such a society within the framework of the *New Deal on Data*, and describe future directions for research and development.

In our view, the traditional control points relied on as part of corporate governance, management oversight, legal compliance, and enterprise architecture must evolve and expand to match operational frameworks for big data. These controls must support and reflect greater user control over personal data, as well as large-scale interoperability for data sharing between and among institutions. The core capabilities of these controls should include responsive rule-based systems governance and fine-grained authorizations for distributed rights management.

The New Realities of Living in a Big Data Society

Building an infrastructure that sustains a healthy, safe, and efficient society is, in part, a scientific and engineering challenge which dates back to the 1800s when the Industrial Revolution spurred rapid urban growth. That growth created new social and environmental problems. The remedy then was to build centralized networks that delivered clean water and safe food, enabled commerce, removed waste, provided energy, facilitated transportation, and offered access to centralized health care, police, and educational services. These networks formed the backbone of society as we know it today.

These century-old solutions are, however, becoming increasingly obsolete and inefficient. We now face the challenges of global warming,

The New Deal on Data: Institutional Controls 193

uncertain energy, water, and food supplies, and a rising population and urbanization that will add 350 million people to the urban population by 2025 in China alone.¹ The new challenge is how to build an infrastructure that enables cities to be energy efficient, have secure food and water supplies, be protected from pandemics, and to have better governance. Big data can enable us to achieve such goals. Rather than static systems separated by function – water, food, waste, transport, education, energy – we can instead regard the systems as dynamic, data-driven networks. Instead of focusing only on access and distribution, we need networked and self-regulating systems, driven by the needs and preferences of citizens – a ‘nervous system’ that maintains the stability of government, energy, and public health systems around the globe. A *control* framework should be established which enables data to be captured about different situations, those observations to be combined with models of demand and dynamic reaction, and the resulting predictions to be used to tune the nervous system to match those needs and preferences.

The engine driving this nervous system is big data: the newly ubiquitous digital data now available about so many aspects of human life. We can analyze patterns of human activity within the digital breadcrumbs we all leave behind as we move through the world: call records, credit card transactions, GPS location fixes, among others.² These data, which record actual activity, may be very different from what we put on Facebook or Twitter; our postings there are what we choose to tell people, edited according to the standards of the day and filtered to match the persona we are building. Although mining social networks can give great insight into human nature,³ the value is limited for operational purposes.⁴

The process of analyzing the patterns within these digital breadcrumbs is called ‘reality mining.’⁵ The Human Dynamics research group at MIT found that these patterns can be used to tell us if we are likely to get diabetes,⁶ or whether we are the sort of person who will pay back loans.⁷ By analyzing them across many people, we are discovering that we can begin to explain many things – crashes, revolutions, bubbles – that previously appeared unpredictable.⁸ For this reason, the magazine *MIT Technology Review* named our development of reality mining one of the 10 technologies that will change the world.⁹

The New Deal on Data

The digital breadcrumbs we leave behind are clues to who we are, what we do, and what we want. This makes personal data – data about individuals – immensely valuable, both for public good and for private companies. As

194 **Greenwood, Stopczynski, Sweatt, Hardjono, and Pentland**

the European Consumer Commissioner, Meglena Kuneva, said recently, “Personal data is the new oil of the Internet and the new currency of the digital world.”¹⁰ The ability to see details of so many interactions is also immensely powerful and can be used for good or for ill. Therefore, protecting personal privacy and freedom is critical to our future success as a society. We need to enable more data sharing for the public good; at the same time, we need to do a much better job of protecting the privacy of individuals.

A successful data-driven society must be able to guarantee that our data will not be abused – perhaps especially that government will not abuse the power conferred by access to such fine-grained data. There are many ways in which abuses might be directly targeted – from imposing higher insurance rates based on individual shopping history,¹¹ to creating problems for the entire society, by limiting user choices and enclosing users in information bubbles.¹² To achieve the potential for a new society, we require the *New Deal on Data*, which describes workable guarantees that the data needed for public good are readily available while at the same time protecting the citizenry.¹³

The key insight behind the New Deal on Data is that our data are worth more when shared. Aggregate data – averaged, combined across population, and often distilled to high-level features – can be used to inform improvements in systems such as public health, transportation, and government. For instance, we have demonstrated that data about the way we behave and where we go can be used to minimize the spread of infectious disease.¹⁴ Our research has also shown how digital breadcrumbs can be used to track the spread of influenza from person to person on an individual level. And the public good can be served as a result: if we can see it, we can also stop it. Similarly, if we are worried about global warming, shared, aggregated data can reveal how patterns of mobility relate to productivity.¹⁵ This, in turn, equips us to design cities that are more productive and, at the same time, more energy efficient. However, to obtain these results and make a greener world, we must be able to see people moving around; this depends on having many people willing to contribute their data, if only anonymously and in aggregate. In addition, the Big Data transformation can help society find efficient means of governance by providing tools to analyze and understand what needs to be done, and to reach consensus on how to do it. This goes beyond simply creating more communication platforms; the assumption that more interaction between users will produce better decisions may be very misleading. Although in recent years we have seen impressive uses of social networks for better organization in society, for

The New Deal on Data: Institutional Controls 195

example during political protests,¹⁶ we are far from even starting to reach consensus about the big problems: epidemics, climate change, pollution – big data can help us achieve such goals.

However, to enable the sharing of personal data and experiences, we need secure technology and regulation that allows individuals to safely and conveniently share personal information with each other, with corporations, and with government. Consequently, the heart of the New Deal on Data must be to provide both regulatory standards and financial incentives enticing owners to share data, while at the same time serving the interests of individuals and society at large. We must promote greater idea flow among individuals, not just within corporations or government departments.

Unfortunately, today most personal data are siloed in private companies and therefore largely unavailable. Private organizations collect the vast majority of personal data in the form of mobility patterns, financial transactions, and phone and Internet communications. These data must not remain the exclusive domain of private companies, because they are then less likely to contribute to the common good; private organizations must be key players in the New Deal on Data. Likewise, these data should not become the exclusive domain of the government. The entities who should be empowered to share and make decisions about their data are the people themselves: users, participants, citizens. We can involve both experts and use the wisdom of crowds – users themselves interested in improving society.

Personal Data: Emergence of a New Asset Class

One of the first steps to promoting liquidity in land and commodity markets is to guarantee ownership rights so that people can safely buy and sell. Similarly, a first step toward creating more ideas and greater flow of ideas – idea liquidity – is to define ownership rights. The only politically viable course is to give individual citizens key rights over data that are about them, the type of rights that have undergirded the European Union's Privacy Directive since 1995.¹⁷ We need to recognize personal data as a valuable asset of the individual, which can be given to companies and government in return for services.

We can draw the definition of ownership from English common law on ownership rights of possession, use, and disposal:

- *You have the right to possess data about yourself.* Regardless of what entity collects the data, the data belong to you, and you can access your data at

196 **Greenwood, Stopczynski, Sweatt, Hardjono, and Pentland**

any time. Data collectors thus play a role akin to a bank, managing data on behalf of their ‘customers’.

- *You have the right to full control over the use of your data.* The terms of use must be opt in and clearly explained in plain language. If you are not happy with the way a company uses your data, you can remove the data, just as you would close your account with a bank that is not providing satisfactory service.
- *You have the right to dispose of or distribute your data.* You have the option to have data about you destroyed or redeployed elsewhere.

Individual rights to personal data must be balanced with the need of corporations and governments to use certain data-account activity, billing information, and the like to run their day-to-day operations. The New Deal on Data therefore gives individuals the right to possess, control, and dispose of copies of these required operational data, along with copies of the incidental data collected about the individual, such as location and similar context. These ownership rights are not exactly the same as literal ownership under modern law; the practical effect is that disputes are resolved in a different, simpler manner than would be the case for land ownership disputes, for example.

In 2007, one author (AP) first proposed the New Deal on Data to the World Economic Forum.¹⁸ Since then, this idea has run through various discussions and eventually helped to shape the 2012 Consumer Data Bill of Rights in the United States, along with a matching declaration on Personal Data Rights in the European Union.

The World Economic Forum (WEF) echoed the European Consumer Commissioner Meglena Kuneva in dubbing personal data the ‘new oil’ or new resource of the 21st century.¹⁹ The ‘personal data sector’ of the economy today is in its infancy, its state akin to the oil industry during the late 1890s. Productive collaboration between government (building the state-owned freeways), the private sector (mining and refining oil, building automobiles), and the citizens (the user-base of these services) allowed developed nations to expand their economies by creating new markets adjacent to the automobile and oil industries.

If personal data, as the new oil, is to reach its global economic potential, productive collaboration is needed between all stakeholders in the establishment of a *personal data ecosystem*. A number of fundamental uncertainties exist, however, about privacy, property, global governance, human rights – essentially about who should benefit from the products and services built on personal data.²⁰ The rapid rate of technological change and

The New Deal on Data: Institutional Controls 197

commercialization in the use of personal data is undermining end-user confidence and trust.

The current personal data ecosystem is feudal, fragmented, and inefficient. Too much leverage is currently accorded to service providers that enroll and register end-users. Their siloed repositories of personal data exemplify the fragmentation of the ecosystem, containing data of varying qualities; some are attributes of persons that are unverified, while others represent higher quality data that have been cross-correlated with other data points of the end-user. For many individuals, the risks and liabilities of the current ecosystem exceed the economic returns. Besides not having the infrastructure and tools to manage personal data, many end-users simply do not see the benefit of fully participating. Personal privacy concerns are thus addressed inadequately at best, or simply overlooked in the majority of cases. Current technologies and laws fall short of providing the legal and technical infrastructure needed to support a well-functioning digital economy.

Recently, we have seen the challenges, but also the feasibility of opening private big data. In the Data for Development (D4D) Challenge (<http://www.d4d.orange.com>), the telecommunication operator Orange opened access to a large dataset of call detail records from the Ivory Coast. Working with the data as part of a challenge, teams of researchers came up with life-changing insights for the country. For example, one team developed a model for how disease spreads in the country and demonstrated that information campaigns based on one-to-one phone conversations among members of social groups can be an effective countermeasure.²¹ Data release must be carefully done, however; as we have seen in several cases, such as the Netflix Prize privacy disaster²² and other similar privacy breaches,²³ true anonymization is extremely hard – recent research by de Montjoye et al. and others^{24,25} has shown that even though human beings are highly predictable, we are also unique. Having access to one dataset may be enough to uniquely fingerprint someone based on just a few data points, and this fingerprint can be used to discover their true identity. In releasing and analyzing the D4D data, the privacy of the people who generated the data was protected not only by technical means, such as removal of personally identifiable information (PII), but also by legal means, with the researchers signing an agreement that they would not use the data for re-identification or other nefarious purposes. Opening data from the silos by publishing static datasets – collected at some point and unchanging – is important, but it is only the first step. We can do even more when data is available in real time and can become part of a society's nervous system.

198 Greenwood, Stopczynski, Sweatt, Hardjono, and Pentland

Epidemics can be monitored and prevented in real time,²⁶ underperforming students can be helped, and people with health risks can be treated before they get sick.²⁷

The report of the World Economic Forum²⁸ suggests a way forward by identifying useful areas on which to focus efforts:

- *Alignment of key stakeholders* Citizens, the private sector, and the public sector need to work in support of one another. Efforts such as NSTIC²⁹ in the United States – albeit still in its infancy – represent a promising direction for global collaboration.
- *Viewing ‘data as money’* There needs to be a new mindset, in which an individual’s personal data items are viewed and treated in the same way as their money. These personal data items would reside in an ‘account’ (like a bank account) where they would be controlled, managed, exchanged, and accounted for just as personal banking services operate today.
- *End-user centricity* All entities in the ecosystem need to recognize end-users as vital and independent stakeholders in the co-creation and exchange of services and experiences. Efforts such as the User Managed Access (UMA) initiative³⁰ provide examples of system design that are user-centric and managed by the user.

Enforcing the New Deal on Data

How can we enforce this New Deal? The threat of legal action is important, but not sufficient; if you cannot see abuses, you cannot prosecute them. Enforcement can be addressed significantly without prosecution or public statute or regulation. In many fields, companies and governments rely on rules governing common business, legal, and technical (BLT) practices to create effective self-organization and enforcement. This approach holds promise as a method by which institutional controls can form a reliable operational framework for big data, privacy, and access.

One current best practice is a system of data sharing called a ‘trust network’, a combination of networked computers and legal rules defining and governing expectations regarding data. For personal data, these networks of technical and legal rules keep track of user permissions for each piece of data and act as a legal contract, specifying what happens in case of a violation. For example, in a trust network all personal data can have attached labels specifying where the data come from and what they can and cannot be used for. These labels are exactly matched by the terms in the legal contracts between all of the participants, stating penalties for not

The New Deal on Data: Institutional Controls 199

obeying them. The rules can – and often do – reference or require audits of relevant systems and data use, demonstrating how traditional internal controls can be leveraged as part of the transition to more novel trust models. A well-designed trust network, elegantly integrating computer and legal rules, allows automatic auditing of data use and allows individuals to change their permissions and withdraw data.

The mechanism for establishing and operating a trust network is to create system rules for the applications, service providers, data, and the users themselves. System rules are sometimes called ‘operating regulations’ in the credit card context, ‘trust frameworks’ in the identity federation context, or ‘trading partner agreements’ in a supply value chain context. Several multiparty shared architectural and contractual rules create binding obligations and enforceable expectations on all participants in scalable networks. Furthermore, the design of the system rules allows participants to be widely distributed across heterogeneous business ownership boundaries, legal governance structures, and technical security domains. However, the parties need not conform in all or even most aspects of their basic roles, relationships, and activities in order to connect to a trust network. Cross-domain trusted systems must – by their nature – focus enforceable rules narrowly on commonly agreed items in order for that network to achieve its purpose.

For example, institutions participating in credit card and automated clearing house networks are subject to profoundly different sets of regulations, business practices, economic conditions, and social expectations. The network rules focus on the topmost agreed items affecting interoperability, reciprocity, risk, and revenue allocation. The knowledge that fundamental rules are subject to enforcement action is one of the foundations of trust and a motivation to prevent or address violations before they trigger penalties. A clear example of this approach can be found in the Visa Operating Rules, which cover a vast global real-time network of parties agreeing to rules governing their roles in the system as merchants, banks, transaction processors, individual or business card holders, and other key system roles.

Such rules have made the interbank money transfer system among the safest systems in the world and the backbone for daily exchanges of trillions of dollars, but until recently those were only for the ‘big guys’.³¹ To give individuals a similarly safe method of managing personal data, the Human Dynamics group at MIT, in partnership with the Institute for Data Driven Design (co-founded by John Clippinger and one author (AP)) have helped to build an open Personal Data Store (openPDS).³² The openPDS is a

200 **Greenwood, Stopczynski, Sweatt, Hardjono, and Pentland**

consumer version of a personal cloud trust network now being tested with a variety of industry and government partners. The aim is to make sharing personal data as safe and secure as transferring money between banks.

When dealing with data intended to be accessible over networks – whether big, personal, or otherwise – the traditional container of an institution makes less and less sense. Institutional controls apply, by definition, to some type of institutional entity such as a business, governmental, or religious organization. A synopsis of all the BLT facts and circumstances surrounding big data is necessary in order to know what access, confidentiality, and other expectations exist; the relevant contextual aspects of big data at one institution are often profoundly different from those at another. As more and more organizations use and rely on big data, a single formula for institutional controls will not work for increasingly heterogeneous BLT environments.

The capacity to apply appropriate methods of enforcement for a trust network depends on clear understanding and agreement among the parties about the purpose of the system and the respective roles or expectations of those connecting as participants. Therefore, some contextual anchor is needed to have a clear basis for establishing an operational framework and institutional controls appropriate for big data.

Transitioning End-User Assent Practices

The way users grant authorization to share their data is not a trivial matter. The flow of personal information such as location data, purchases, and health records can be very complex. Every tweet, geotagged picture, phone call, or purchase with credit card provides the user's location not only to the primary service, but also to all the applications and services that have been authorized to access and reuse these data. The authorization may come from the end-user or be granted by the collecting service, based on umbrella terms of service that cover reuse of the data. Implementation of such flows was a crucial part of the Web 2.0 revolution, realized with RESTful APIs, mash-ups, and authorization-based access. The way personal data travels between services has arguably become too complex for a user to handle and manage.

Increasing the range of data controlled by the user and the granularity of this control is meaningless if it cannot be exercised in an informed way. For many years, a poor model has been provided by End User License Agreements (EULAs), long incomprehensible texts that are accepted blindly by users trusting they have not agreed to anything that could harm them. The

The New Deal on Data: Institutional Controls 201

process of granting meaningful authorization cannot be too complex, as it would prevent a user from understanding her decisions. At the same time, it cannot be too simplistic, as it may not sufficiently convey the weight of the privacy-related decisions it captures. It is a challenge in itself to build end-user assent systems that allow users to understand and adjust their privacy settings.

This gap between the interface – single click – and the effect can render data ownership meaningless; one click may wrench people and their data into systems and rules that are antithetical to fair information practices, as is prevalent with today's end-user licenses in cloud services or applications. Managing the long-term tensions fueled by 'old deal' systems operating simultaneously with the New Deal is an important design and migration challenge during the transition to a Big Data economy. During this transition and after the New Deal on Data is no longer new, personal data must continue to flow in order to be useful. Protecting the data of people outside of directly user-controlled domains is very hard without a combination of cost-effective and useful business practices, legal rules, and technical solutions.

We envision 'living informed consent', where the user is entitled to know what data is being collected about her by which entities, empowered to understand the implications of data sharing, and finally put in charge of the sharing authorizations. We suggest that readers ask themselves a question: *Which services know which city I am in today?* Google? Apple? Twitter? Amazon? Facebook? Flickr? Some app I authorized a few years ago to access my Facebook check-ins and have since forgotten about? This is an example of a fundamental question related to user privacy and assent, and yet finding an accurate answer can be surprisingly difficult in today's ecosystem. We can hope that most services treat data responsibly and according to user authorizations. In the complex network of data flows, however, it is relatively easy for data to leak to careless or malicious services.³³ We need to build solutions that help users to make well-informed decisions about data sharing in this environment.

Big Data and Personal Data Institutional Controls

The concept of 'institutional controls' refers to safeguards and protections implemented through legal, policy, governance, and other measures that are not solely technical, engineering, or mechanical. Institutional controls in the context of big data can perhaps best be understood by examining how such controls have been applied to other domains, most prevalently in

202 Greenwood, Stopczynski, Sweatt, Hardjono, and Pentland

the field of environmental regulation. A good example of how this concept supports and reflects the goals and objectives of environmental regulation can be found in the policy documents of the Environmental Protection Agency (EPA), which gives the following definition in its Institutional Controls Glossary:

Institutional Controls – Non-engineering measures intended to affect human activities in such a way as to prevent or reduce exposure to hazardous substances. They are almost always used in conjunction with, or as a supplement to, other measures such as waste treatment or containment. There are four categories of institutional controls: governmental controls; proprietary controls; enforcement tools; and informational devices.³⁴

The concept of an ‘institutional control boundary’ is especially clarifying and powerful when applied to the networked and digital boundaries of an institution. In the context of Florida’s environmental regulation, the phrase is applied when a property owner’s risk management and clean-up responsibilities extend beyond the area defined by the physical property boundary. For example, a recent University of Florida report on clean-up target levels (CTLs) states, “in some rare situations, the institutional control boundary at which default CTLs must be met can extend beyond the site property boundary.”³⁵

When institutional controls apply to “separately owned neighboring properties” a number of possibilities arise that are very relevant to management of personal data across legal, business, and other systemic boundaries. Requiring the party responsible for site clean-up to use “best efforts” to attain agreement from the neighboring owners to institute the relevant institutional controls is perhaps the most direct and least prescriptive approach. When direct negotiated agreement is unsuccessful, then use of third-party neutrals to resolve disagreements regarding institutional controls can be required. If necessary, environmental regulation can force the acquisition of neighboring land by compelling the party responsible to purchase the other property or by purchase of the property directly by the EPA.³⁶

In the context of big data, institutional controls are seldom, if ever, imposed through government regulatory frameworks such as are seen in environmental waste management oversight by the EPA.³⁷ Rather, institutions applying measures constituting institutional controls in the big data and related information technology and enterprise architecture contexts will typically employ governance safeguards, business practices, legal

The New Deal on Data: Institutional Controls 203

contracts, technical security, reporting, and audit programs and various risk management measures.

Inevitably, institutional controls for big data will have to operate effectively across institutional boundaries, just as environmental waste management must sometimes be applied across real property boundaries and may subject multiple different owners to enforcement actions corresponding to the applicable controls. Short of government regulation, the use of system rules as a general model is one widely understood, accepted, and efficient method for defining, agreeing, and enforcing institutional and other controls across BLT domains of ownership, governance, and operation.

Following on from the World Economic Forum's recommendation to treat personal data stores in the manner of bank accounts,³⁸ a number of infrastructure improvements need to be realized if the personal data ecosystem is to flourish and deliver new economic opportunities:

- *New global data provenance network* In order for personal data stores to be treated like bank accounts, origin information regarding data items coming into the data store must be maintained.³⁹ In other words, the provenance of all data items must be accounted for by the IT infrastructure on which the personal data store operates. The databases must then be interconnected in order to provide a resilient, scalable platform for audit and accounting systems to track and reconcile the movement of personal data from different data stores.
- *Trust network for computational law* For trust to be established between parties who wish to exchange personal data, some degree of 'computational law' technology may have to be integrated into the design of personal data systems. This technology should not only verify terms of contracts (e.g. terms of data use) against user-defined policies but also have mechanisms built in to ensure non-repudiation of entities who have accepted these digital contracts. Efforts such as the UMA initiative are beginning to bring better evidentiary proof and enforceability of contracts into technical protocol flows.⁴⁰
- *Development of institutional controls for digital institutions* Currently, a number of proposals for the creation of virtual currencies (e.g. BitCoin,⁴¹ Ven⁴²) have underlying systems with the potential to evolve into self-governing 'digital institutions'.⁴³ Such systems and the institutions that operate on them will necessitate the development of a new paradigm to understand aspects of institutional control within their context.

204 Greenwood, Stopczynski, Sweatt, Hardjono, and Pentland

Scenarios of Use in Context

Developing frameworks for big data that effectively balance economic, legal, security, and other interests requires an understanding of the relevant context and applicable scenarios within which the data exists.

A sound starting point from which to establish the applicable scenarios of use is to enumerate the institutions involved with a given set of big data, and develop a description of how or why they hold, access, or otherwise intermediate the data. Although big data straddles multiple BLT boundaries, one or more institutions are typically able to, or in some situations required to, manage and control the data. The public good referred to in the title of this book can be articulated as design requirements or even as certification criteria applicable to those institutions that operate the systems through which the big data is computed or flows.

It may be also be necessary to narrowly define certain aspects of the scenario in which the data exist in order to establish the basic ownership, control, and other expectations of the key parties. For example, describing a transaction as a financial exchange may not provide enough relevant detail to reveal the rights, obligations, or other outcomes reasonably expected by the individuals and organizations involved. The sale of used cars via an app, the conduct of a counseling session via Google Hangout, and the earning of a master's degree via an online university all represent scenarios in which the use case of a financial exchange takes place. However, each of these scenarios occurs in a context that is easily identifiable: the sale of goods and deeper access to financial information if the car is financed; the practice of therapy by a licensed professional accessing and creating confidential mental health data; or e-learning services and protected educational records and possibly deeper financial information if the program is funded by scholarship or loans. The scenarios can also identify the key elements necessary to establish existing consumer rights – the people (a consumer and a used car dealer), the transaction (purchase of a used car), the data (sales and title data, finance information, etc.), and the systems (the third-party app and its relevant services or functions, state DMV services, credit card and bank services, etc.). The rights established by relevant state lemon laws, the Uniform Commercial Code, and other applicable rules will determine when duties arise or are terminated, what must be promised, what can be repudiated, by whom data must be kept secure, and other requirements or constraints on the use of personal data and big data. These and other factors differ when a transaction that seems identical operates within a different scenario, and even scenarios will differ depending on which contexts apply.

The New Deal on Data: Institutional Controls 205

The following four elements are critical for defining high-level goals and objectives:

1. Who are the *people* in the scenario (e.g. who are the parties involved and what are their respective roles and relationships)?
2. What are the relevant *interactions* (e.g. what transactions or other actions are conducted by or with the people involved)?
3. What are the relevant *data* and datasets (e.g. what types of data are created, stored, computed, transmitted, modified, or deleted)?
4. What are the relevant *systems* (e.g. what services or other software are used by the people, for the transactions, or with the data)?

Inspired by common law, the New Deal on Data sets out general principles of ownership that both guide and inform basic relationships and expectations. However, the dynamic bundle of recombinant rights and responsibilities constituting ‘ownership’ interests in personal data and expectations pertaining to big data vary significantly from context to context, and even from one scenario to another within a given general context. Institutional controls and other system safeguards are important methods to ensure that there are context-appropriate outcomes that are consistent with clearly applicable system scenarios as well as the contours and foundations for a greater public good. The New Deal on Data can be achieved in part by sets of institutional controls involving governance, business, legal, and technical aspects of big data and interoperating systems. Reference scenarios can be used to reveal signature features of the New Deal on Data in various contexts and can serve as anchors in evaluating what institutional controls are well aligned to achieve a balance of economic, privacy, and other interests.

The types of requirements and rules governing participation by individuals and organizations in trust networks vary depending on the facts and circumstances of the transactions, data types, relevant roles of people, and other factors. Antecedent but relevant networks such as credit card systems, trading partner systems, and exchange networks are instructive not only for their many common elements but also as important examples of how vastly different they are from one another in their contexts, scenarios, legal obligations, business models, technical processes, and other signature patterns. Trust networks that are formed to help manage big data in ways that appropriately respect personal data rights and other broader interests will similarly succeed to the extent they can tolerate or promote a wide degree of heterogeneity among participants for BLT matters that need not be uniform or directly harmonized. In some situations, new business

206 Greenwood, Stopczynski, Sweatt, Hardjono, and Pentland

models and contexts will emerge that require fresh thinking and novel combinations of roles or types of relationships among transacting parties. In these cases, understanding the actual context and scenarios is critical in customizing acceptable and sustainable BLT rules and systems. Example scenarios can describe deeper fact-based situations and circumstances in the context of social science research involving personal data and big data.⁴⁴ The roles of people, their interactions, the use of data, and the design of the corresponding systems reflect and support the New Deal on Data in ways that deliberately provide greater immediate value to stakeholders than is typically expected.

The New Deal on Data is designed to provide good value to anyone creating, using, or benefiting from personal data, but the vision need not be adopted in its entirety before its value becomes apparent. Its principles can be adopted on a large scale in increments – an economic sector, transaction type, or data type at a time. Adopting the New Deal on Data in successive phases helps to address typical objections to change based on cost, disruption, or overregulation. Policy incentives can further address these objections, for example by allowing safe harbor protections for organizations operating under the rules of a trust network.

Predesigned use cases can provide benchmarks for determining whether given uses of personal data are consistent with measurable criteria. Such criteria can be used to establish compliance with the rules of a trust network and for certification by government for the right to safe harbor or other protections. Because the New Deal on Data is rooted in common law and the social compact, the appropriate set of rights and expectations covering privacy and other personal data interests can be enumerated, debated, and agreed upon in ways that fit the given use cases.

Conclusions

Society today faces unprecedented challenges and meeting them will require access to personal data, so we can understand how society works, how we move around, what makes us productive, and how everything from ideas to diseases spread. The insights must be actionable and available in real time, thus engaging the population, creating the nervous system of the society. In this chapter we have reviewed how big data collected in institutional contexts can be used for the public good. In many cases, although the data needed to create a better society has already been collected, it sits in the closed silos of companies and governments. We have described how the silos can be opened using well-designed and carefully

The New Deal on Data: Institutional Controls 207

implemented sets of institutional controls, covering business, legal, and technical dimensions. The framework for doing this – the New Deal on Data – postulates that the primary driver of change must be recognizing that ownership of personal data rests with the people that data is about. This ownership – the right to use, transfer, and remove the data – ensures that the data is available for the public good, while at the same time protecting the privacy of citizens.

The New Deal on Data is still new. We have described here our efforts to understand the technical means of its implementation, the legal framework around it, its business ramifications, and the direct value of the greater access to data that it enables. It is clear that companies must play the major role in implementing the New Deal, incentivized by business opportunities, guided by legislation, and pressured by demands from users. Only with such orchestration will it be possible to modernize the current system of data ownership and put immense quantities and capabilities of collected personal data to good use.

NOTES

1. Jonathan Woetzel et al., “Preparing for China’s Urban Billion” (McKinsey Global Institute, March 2009), http://www.mckinsey.com/insights/urbanization/preparing_for_urban_billion_in_china.
2. David Lazer, Alex Sandy Pentland, Lada Adamic, Sinan Aral, Albert Laszlo Barabasi, Devon Brewer, Nicholas Christakis, Noshir Contractor, James Fowler, and Myron Gutmann, “Life in the Network: The Coming Age of Computational Social Science,” *Science* 323 (2009): 721–723.
3. Sinan Aral and Dylan Walker, “Identifying Influential And Susceptible Members Of Social Networks,” *Science* 337 (2012): 337–341; Alan Mislove, Sune Lehmann, Yong-Yeol Ahn, Jukka-Pekka Onnela, and J. Niels Rosenquist, *Pulse of the Nation: U.S. Mood throughout the Day Inferred from Twitter* (website), <http://www.ccs.neu.edu/home/amislove/twittermood/> (accessed November 22, 2013); Jessica Vitak, Paul Zube, Andrew Smock, Caleb T. Carr, Nicole Ellison, and Cliff Lampe, “It’s Complicated: Facebook Users’ Political Participation in the 2008 Election,” *Cyberpsychology, Behavior, and Social Networking* 14 (2011): 107–114.
4. Alexis Madrigal, “Dark Social: We Have the Whole History of the Web Wrong,” *The Atlantic*, October 12, 2013, <http://www.theatlantic.com/technology/archive/2012/10/dark-social-we-have-the-whole-history-of-the-web-wrong/263523/>.
5. Nathan Eagle and Alex Pentland, “Reality Mining: Sensing Complex Social Systems,” *Personal and Ubiquitous Computing* 10 (2006): 255–268; Alex Pentland, “Reality Mining of Mobile Communications: Toward a New Deal on Data,” *The Global Information Technology Report 2008–2009* (Geneva: World Economic Forum, 2009), 75–80.

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208 Greenwood, Stopczynski, Sweatt, Hardjono, and Pentland

6. Alex Pentland, David Lazer, Devon Brewer, and Tracy Heibeck, "Using Reality Mining to Improve Public Health and Medicine," *Studies in Health Technology and Informatics* 149 (2009): 93–102.
7. Vivek K. Singh, Laura Freeman, Bruno Lepri, and Alex Sandy Pentland, "Classifying Spending Behavior using Socio-Mobile Data," *HUMAN2* (2013): 99–111.
8. Wei Pan, Yaniv Althshuler, and Alex Sandy Pentland, "Decoding Social Influence and the Wisdom of the Crowd in Financial Trading Network," in *2012 International Conference on Privacy, Security, Risk and Trust (PASSAT), and 2012 International Conference on Social Computing (SocialCom)*, 203–209.
9. Kate Greene, "Reality Mining," *MIT Technology Review*, March/April 2008, <http://pubs.media.mit.edu/pubs/papers/tr10pdfdownload.pdf>.
10. Meglena Kuneva, European Consumer Commissioner, "Keynote Speech," in *Roundtable on Online Data Collection, Targeting and Profiling*, March 31, 2009, <http://europa.eu/rapid/press-release.SPEECH-09-156.en.htm>.
11. Kim Gittleston, "How Big Data Is Changing The Cost Of Insurance," *BBC News*, November 14, 2013, <http://www.bbc.co.uk/news/business-24941415>.
12. Aniko Hannak, Piotr Sapiezynski, Kakhki Arash Molavi, Balachander Krishnamurthy, David Lazer, Alan Mislove, and Christo Wilson, "Measuring Personalization of Web Search," in *Proc. 22nd International Conference on World Wide Web (WWW 2013)*, 527–538.
13. Pentland, "Reality Mining of Mobile Communications."
14. Anmol Madan, Manuel Cebrian, David Lazer, and Alex Pentland, "Social Sensing for Epidemiological Behavior Change," in *Proc. 12th ACM International Conference on Ubiquitous Computing (UbiComp 2010)*, 291–300; Pentland et al. "Using Reality Mining to Improve Public Health and Medicine."
15. Wei Pan, Gourab Ghoshal, Coco Krumme, Manuel Cebrian, and Alex Pentland, "Urban Characteristics Attributable to Density-Driven Tie Formation," *Nature Communications* 4 (2013): article 1961.
16. Lev Grossman, "Iran Protests: Twitter, the Medium of the Movement," *Time Magazine*, June 17, 2009; Ellen Barry, "Protests in Moldova Explode, with Help of Twitter," *The New York Times*, April 8, 2009.
17. "Directive 95/46/EC of the European Parliament and of the Council of 24 October 1995 on the Protection of Individuals with Regard to the Processing of Personal Data and on the Free Movement of Such Data," *Official Journal L281* (November 23, 1995): 31–50.
18. World Economic Forum, "Personal Data: The Emergence of a New Asset Class," January 2011, <http://www.weforum.org/reports/personal-data-emergence-new-asset-class>.
19. Ibid.
20. Ibid.
21. Antonio Lima, Manlio De Domenico, Veljko Pejovic, and Mirco Musolesi, "Exploiting Cellular Data for Disease Containment and Information Campaign Strategies in Country-Wide Epidemics," School of Computer Science Technical Report CSR-13-01, University of Birmingham, May 2013.
22. Arvind Narayanan and Vitaly Shmatikov, "Robust De-Anonymization of Large Sparse Datasets," in *Proc. 2008 IEEE Symposium on Security and Privacy (SP)*, 111–125.

The New Deal on Data: Institutional Controls 209

23. Latanya Sweeney, "Simple Demographics Often Identify People Uniquely," Data Privacy Working Paper 3, Carnegie Mellon University, Pittsburgh, 2000.
24. de Montjoye, Yves-Alexandre, Samuel S. Wang, Alex Pentland, "On the Trusted Use of Large-Scale Personal Data," *IEEE Data Engineering Bulletin* 35, no. 4 (2012): 5–8.
25. Chaoming Song, Zehui Qu, Nicholas Blumm, and Albert-Laszlo Barabasi, "Limits of Predictability in Human Mobility," *Science* 327 (2010): 1018–1021.
26. Pentland et al., "Using Reality Mining to Improve Public Health and Medicine."
27. David Tacconi, Oscar Mayora, Paul Lukowicz, Bert Arnrich, Cornelia Setz, Gerhard Troster, and Christian Haring, "Activity and Emotion Recognition to Support Early Diagnosis of Psychiatric Diseases," in *Proc. 2nd International ICST Conference on Pervasive Computing Technologies for Healthcare*, 100–102.
28. World Economic Forum, "Personal Data."
29. The White House, "National Strategy for Trusted Identities in Cyberspace: Enhancing Online Choice, Efficiency, Security, and Privacy," Washington, DC, April 2011, http://www.whitehouse.gov/sites/default/files/rss_viewer/NSTICstrategy_041511.pdf.
30. Thomas Hardjono, "User-Managed Access UMA Profile of OAuth2.0," Internet draft, 2013, <http://docs.kantarinitiative.org/uma/draft-uma-core.html>.
31. A Creative Commons licensed example set of integrated business and technical system rules for the institutional use of personal data stores is available at <https://github.com/HumanDynamics/SystemRules>.
32. See <http://openPDS.media.mit.edu> for project information and <https://github.com/HumanDynamics/openPDS> for the open source code.
33. Nick Bilton, "Girls around Me: An App Takes Creepy to a New Level," *The New York Times, Bits* (blog), March 30, 2012, <http://bits.blogs.nytimes.com/2012/03/30/girls-around-me-ios-app-takes-creepy-to-a-new-level>.
34. U.S. Environmental Protection Agency, RCRA Corrective Action Program, "Institutional Controls Glossary," Washington, DC, 2007, <http://www.epa.gov/epawaste/hazard/correctiveaction/resources/guidance/ics/glossary1.pdf>.
35. University of Florida, Center for Environmental & Human Toxicology, "Development of Cleanup Target Levels (CTLs) for Chapter 62-777, F.A.C.," Technical report, Florida Department of Environmental Protection, Division of Waste Management, February 2005, [http://www.dep.state.fl.us/waste/quick_topics/publications/wc/FinalGuidanceDocumentsFlowCharts_April2005/TechnicalReport2FinalFeb2005\(Final3-28-05\).pdf](http://www.dep.state.fl.us/waste/quick_topics/publications/wc/FinalGuidanceDocumentsFlowCharts_April2005/TechnicalReport2FinalFeb2005(Final3-28-05).pdf).
36. U.S. Environmental Protection Agency, "Institutional Controls: A Guide to Planning, Implementing, Maintaining, and Enforcing Institutional Controls at Contaminated Sites," OSWER 9355.0-89, Washington, DC, December 2012, <http://www.epa.gov/superfund/policy/ic/guide/Final%20PIME%20Guidance%20December%202012.pdf>.
37. Ralph A. DeMeo and Sarah Meyer Doar, "Restrictive Covenants as Institutional Controls for Remediated Sites: Worth the Effort?" *The Florida Bar Journal* 85, no. 2 (February 2011); Florida Department of Environmental Protection, Division of Waste Management, "Institutional Controls Procedures Guidance," Tallahassee, June 2012, http://www.dep.state.fl.us/waste/quick_topics/publications/wc/csf/icpg.pdf; University of Florida, "Development of Cleanup Target Levels."

210 **Greenwood, Stopczynski, Sweatt, Hardjono, and Pentland**

38. World Economic Forum, "Personal Data."
39. Thomas Hardjono, Daniel Greenwood, and Alex Pentland, "Towards a Trustworthy Digital Infrastructure for Core Identities and Personal Data Stores," in *Proc. ID360 Conference on Identity*, 2013.
40. Hardjono, "User-Managed Access UMA Profile of OAuth2.0"; Eve Maler and Thomas Hardjono, "Binding Obligations on User-Managed Access (UMA) Participants," Internet draft, 2013, <http://docs.kantarinitiative.org/uma/draft-uma-trust.html>.
41. Simon Barber, Xavier Boyen, Elaine Shi, and Ersin Uzun, "Bitter to Better – How to Make Bitcoin a Better Currency," in *Proc. Financial Cryptography and Data Security Conference (2012)*, LNCS 7397, 399–414.
42. Stan Stalnaker, "About [Ven Currency]," <http://www.ven.vc> (accessed January 16, 2014).
43. Thomas Hardjono, Patrick Deegan, and John Clippinger, "On the Design of Trustworthy Compute Frameworks for Self-Organizing Digital Institutions," in *Proc. 16th International Conference on Human-Computer Interaction (2014)*, forthcoming; Lazer et al., "Life in the Network."
44. See e.g. the study SensibleDTU (<https://www.sensible.dtu.dk/?lang=en>). This study of 1,000 freshman students at the Technical University of Denmark gives students mobile phones in order to study their networks and social behavior during an important change in their lives. It uses not only data collected from the mobile phones (such as location, Bluetooth-based proximity, and call and sms logs), but also from social networks and questionnaires filled out by participants.

APPENDIX B

Measuring large-scale social networks with high resolution

Arkadiusz Stopczynski, Vedran Sekara, Piotr Sapiezynski, Andrea Cuttone, Mette My Madsen, Jakob Eg Larsen, and Sune Lehmann. Measuring Large-Scale Social Networks with High Resolution. *Under Review in PLOS ONE*. arXiv preprint arXiv:1401.7233 (2014).

Measuring Large-Scale Social Networks with High Resolution

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Contents

| | | |
|----------|--|-----------|
| 1 | Abstract | 3 |
| 2 | Introduction | 3 |
| 3 | Related Work | 5 |
| 3.1 | Data collection | 5 |
| 3.2 | Data analysis | 6 |
| 3.2.1 | Human Mobility | 6 |
| 3.2.2 | Social Interactions | 6 |
| 3.2.3 | Health and Public Safety | 6 |
| 3.2.4 | Influence and Information Spread | 7 |
| 3.2.5 | Socioeconomics and Organizational Behavior | 7 |
| 3.3 | Privacy | 7 |
| 4 | Motivation | 8 |
| 4.1 | Multiplexity | 8 |
| 4.2 | Sampling | 9 |
| 4.3 | Dynamics | 9 |
| 4.4 | Feedback | 10 |
| 4.5 | New Science | 10 |
| 5 | Methods: Data Collection | 11 |
| 5.1 | Data Sources | 11 |
| 5.1.1 | Questionnaires | 12 |
| 5.1.2 | Facebook Data | 12 |
| 5.1.3 | Sensor Data | 12 |
| 5.1.4 | Qualitative Data | 13 |
| 5.1.5 | WiFi Data | 13 |
| 5.2 | Backend System | 14 |
| 5.2.1 | The 2012 Deployment | 14 |
| 5.2.2 | The 2013 Deployment | 14 |
| 5.3 | Deployment Methods | 14 |
| 5.3.1 | SensibleDTU 2012 | 14 |
| 5.3.2 | SensibleDTU 2013 | 15 |
| 6 | Methods: Privacy | 16 |

| | |
|---|-----------|
| | 2 |
| 7 Results | 17 |
| 7.1 Bluetooth and Social Ties | 18 |
| 7.2 WiFi as an Additional Channel for Social Ties | 20 |
| 7.3 Location and Mobility | 23 |
| 7.4 Call & Text Communication Patterns | 24 |
| 7.5 Online friendships | 27 |
| 7.6 Personality traits | 29 |
| 8 Perspectives | 29 |
| 9 Acknowledgments | 31 |

1 Abstract

This paper describes the deployment of a large-scale study designed to measure human interactions across a variety of communication channels, with high temporal resolution and spanning multiple years—the Copenhagen Networks Study. Specifically, we collect data on face-to-face interactions, telecommunication, social networks, location, and background information (personality, demographics, health, politics) for a densely connected population of 1000 individuals, using state-of-the-art smartphones as social sensors. Here we provide an overview of the related work and describe the motivation and research agenda driving the study. Additionally, the paper details the data-types measured, and the technical infrastructure in terms of both backend and phone software, as well as an outline of the deployment procedures. We document the participant privacy procedures and their underlying principles. The paper is concluded with early results from data analysis, illustrating the importance of multi-channel high-resolution approach to data collection.

2 Introduction

Driven by the ubiquitous availability of data and inexpensive data storage capabilities, the concept of big data has permeated the public discourse and led to surprising insights across the sciences and humanities [1, 2]. While collecting data may be relatively easy, it is a challenge to combine datasets from multiple sources. This is in part due to mundane practical issues, such as matching up noisy and incomplete data, and in part due to complex legal and moral issues connected to data ownership and privacy, since many datasets contain sensitive data regarding individuals [148]. As a consequence, most large datasets are currently locked in ‘silos’, owned by governments or private companies, and in this sense the big data we use today are ‘shallow’—only a single or very few channels are typically examined.

Such shallow data limit the results we can hope to generate from analyzing these large datasets. We argue below (in Motivation Section) that in terms of understanding of human social networks, such shallow big data sets are not sufficient to push the boundaries in certain areas. The reason is that human social interactions take place across various communication channels; we seamlessly and routinely connect to the same individuals using face-to-face communication, phone calls, text messages, social networks (such as Facebook and Twitter), emails, and many other platforms. Our hypothesis is that, in order to understand social networks, we must study communication across these many channels that are currently siloed. Existing big data approaches have typically concentrated on large populations ($\mathcal{O}(10^5) - \mathcal{O}(10^8)$), but with a relatively low number of bits per participant, for example in call detail records (CDR) studies [3] or Twitter analysis [4]. Here, we are interested in capturing deeper data, looking at multiple channels from sizable populations. Using big data collection and analysis techniques that can scale in number of participants, we show how to start deep, i.e. with detailed information about every single study participant, and then scale up to very large populations.

We are not only interested in collecting deep data from a large, highly connected population, but we also aim to create a dataset that is collected interactively, allowing us to change the collection process. This enables us to rapidly adapt and change our collection methods if current data, for example, have insufficient temporal resolution with regard to a specific question we would like to answer. We have designed our data collection setup in such a way that we are able to deploy experiments. We have done this because we know that causal inference is notoriously complicated in network settings [5]. Moreover, our design allows us to perform continuous quality control of the data collected. The mindset of real-time data access can be extended beyond pure research, monitoring data quality and performing interventions. Using the methods described here, we can potentially use big data in real time to observe and react to the processes taking place across entire societies. In order to achieve this goal, researchers must approach the data in the same way large Internet services do—as a resource that can be manipulated and made available in real time as this kind of data inevitably loses value over time.

In order to realize the interactive data collection, we need to build long-lasting testbeds to rapidly deploy experiments, while still retaining access to all the data collected hitherto. Human beings are not static; our behavior, our networks, our thinking change over time [6, 7]. To be able to analyze and understand changes over long time scales, we need longitudinal data, available not just to a single group of researchers, but to changing teams of researchers who work with an evolving set of ideas, hypotheses, and perspectives. Ultimately, we aim to be able to access the data containing the entire life-experience of people and look at their lives as dynamic processes. Eventually, we aim to even go beyond the lifespan of individuals and analyze the data of the entire generations. We are not there yet, but we are moving in this direction. For example, today, all tweets are archived in the Library of Congress (<https://blog.twitter.com/2010/tweet-preservation>), a person born today in a developed country has a good chance of keeping every single picture they ever take, the next generation will have a good chance of keeping highly detailed life-log, including, for example, every single electronic message they have ever exchanged with their friends. The status quo is that we need to actively opt out if we want to prevent our experiences from being auto-shared: major cloud storage providers offer auto-upload feature for pictures taken with a smartphone, every song we listen to on Spotify is remembered and used to build our profile—unless we actively turn on private mode.

In this paper, we describe a large-scale study that observes the lives of students through multiple channels—the Copenhagen Network Study. With its iterative approach to deployments, this study provides an example of an interdisciplinary approach. We collect data from multiple sources, including questionnaires, online social networks, and smartphones handed out to the students. Data from all of these channels are used to create a multi-layered view of the individuals, their networks, and their environments. These views can then be examined separately, and jointly, by researchers from different fields. We are building the Copenhagen Networks Study as a framework for long-lived extensible studies. The 2012 and 2013 deployments described here are called *SensibleDTU* and are based at the Technical University of Denmark. They have been designed as part of the *Social Fabric* project (see Acknowledgements for details) in close collaboration with researchers from the social sciences, natural sciences, medicine (public health), and the humanities. We are currently in the second iteration where we have deployed phones to about 1000 participants, enabling us to compile a dataset of unprecedented size and resolution. In addition to the core task of collecting deep behavioral data, we also experiment with creating rich services for our participants and improving privacy practices.

Human lives, especially when seen over a period of months and years, take place in multiple dimensions. Capturing only a single channel, even for the entire life of an individual, limits the knowledge that can be applied to understand a human being. True interdisciplinary studies require deep data. Anthropologists, economists, philosophers, physicists, psychologists, public health researchers, sociologists, and computational social science researchers are all interested in distinct questions, and traditionally use very different methods. We believe that it is when these groups start working together, qualitatively better findings can be made.

Here we give a brief overview of the related work, in the domains of data collection and analysis, extend the description of the motivation driving the project, and outline the experimental plan and data collection methodology. We report on privacy and informed consent practices that are used in the study, emphasizing how we went beyond the usual practice in such studies and created some cutting edge solutions in the domain. We also report a few initial results from the project, primarily in the form of an overview of collected data, and outline future directions. We hope the work presented here will serve as a guideline for deploying similar massive sensor-driven human-data collection studies. With the overview of the collected data, we extend an invitation to researchers of all fields to contact the authors for the purpose of defining novel projects around the Copenhagen Networks Study testbed.

3 Related Work

Lazer et al. introduced computational social science (CSS) as a new field of research that studies individuals and groups in order to understand populations, organizations, and societies using big data, i.e. phone call records, GPS traces, credit card transactions, webpage visits, emails, and data from social networks [8]. CSS focuses on questions that can now be studied using data-driven computational analyses of datasets such as the ones mentioned above, and which could only previously be addressed as self-reported data or direct observations, for example dynamics in work groups, face-to-face interactions, human mobility, or information spreading. The hope is that such a data-driven approach will bring new types of insight that are not available using traditional methods. The challenges that emerge in this set of new approaches include wrangling big data, applying network analysis to dynamic networks, ensuring privacy of personal information, and enabling interdisciplinary work between computer science and social science, to name just a few.

In this section we describe related work in terms of the central methods of data collection. Furthermore, we provide a brief overview of results obtained from the analysis of CSS data, and finally, mention some principles regarding privacy and data treatment.

3.1 Data collection

Many of the CSS studies carried out to date have been performed on call detail records (CDRs), which are records of phone calls and messages collected by mobile phone operators. Although CDRs can be a proxy for mobility and social interaction [9], much of the social interaction happens face-to-face, and may therefore be difficult to capture with CDRs or other channels such as social networks (Twitter, Facebook, etc.) [10]. To gain a fuller view of participants' behavior, some CSS studies have developed an approach of employing Radio Frequency Identification (RFID) devices [11], sociometric badges [12, 13], as well as smartphones for the data collection [14–17]. Smartphones are unobtrusive, relatively cheap, feature a plethora of embedded sensors, and tend to travel nearly everywhere with their users. They allow for automatic collection of sensor data including GPS, WiFi, Bluetooth, calls, SMS, battery, and application usage [18]. However, collecting data with smartphones presents several limitations as sensing is mainly limited to pre-installed sensors, which may not be of highest quality. Furthermore, off-the-shelf software and hardware may not be sufficiently robust for longitudinal studies.

A large number of solutions for sensor-driven human data collection have been developed, ranging from dedicated software to complete platforms, notably ContextPhone [19], SocioXensor [20], MyExperience [21], Anonymsense [22], CenceMe [23], Cityware [24], Darwin phones [25], Vita [26], and Context-Toolbox [27].

Running longitudinal rich behavioral data collection from large populations presents multiple logistical challenges and only few studies have attempted to do this so far. In the Reality Mining study, data from 100 mobile phones were collected over a nine-month period [28]. In the Social fMRI study, 130 participants carried smartphones running the Funf mobile software [29] for 15 months [30]. Data was also collected from Facebook, credit card transactions, and surveys were pushed to the participants' phones. The Lausanne Data Collection Campaign [31, 32] featured 170 volunteers in the Lausanne area of Switzerland, between October 2009 and March 2011. In the SensibleOrganization study [33], researchers used RFID tags for a period of one month to collect face-to-face interactions of 22 employees working in a real organization. Preliminary results from the OtaSizzle study covering 20 participants from a large university campus have been reported [34]. Finally, in the Locaccino study [35], location within a metropolitan region was recorded for 489 participants for varying periods, ranging from seven days to several months.

3.2 Data analysis

In the following, we provide selected examples of results obtained from analysis of CSS datasets in various domains.

3.2.1 Human Mobility

Gonzales et al. analyzed six months of CDRs of 100 000 users. Their results revealed that human mobility is quite predictable, with high spatial and temporal regularity, and few highly frequented locations [36]. Their findings were further explored by Song et al., who analyzed three months of CDRs from 50 000 individuals and found a 93% upper bound of predictability of human mobility. This figure applies to most users regardless of different travel patterns and demographics [37]. Sevtsuk et al. focused instead on the aggregate usage of 398 cell towers, describing the hourly, daily, and weekly patterns and their relation to demographics and city structure [38]. Bagrow et al. analyzed 34 weeks of CDRs for 90 000 users, identifying habitats (groups of related places) and found that the majority of individuals in their dataset had between 5 and 20 habitats [39]. De Domenico et al. showed in [40] how location prediction can be performed using multivariate non-linear time series prediction, and how accuracy can be improved considering the geo-spatial movement of other users with correlated mobility patterns.

3.2.2 Social Interactions

Face-to-face interactions can be used to model social ties over time and organizational rhythms in response to events [28, 41, 42]. Comparing these interactions with Facebook networks, Cranshaw et al. found that meetings in locations of high entropy (featuring a diverse set of visitors) are less indicative than meetings in locations visited by a small set of users [35]. Clauset et al. found that a natural time scale of face-to-face social networks is 4 hours [43].

Onnela et al. analyzed CDRs from 3.9 million users [44] and found evidence supporting the weak ties hypothesis [45]. Lambiotte et al. analyzed CDRs from 2 million users and found that the probability of the existence of the links decreases as d^{-2} , where d is the distance between users [46]. In another study with CDRs from 3.4 million users, the probability was found to decrease as $d^{-1.5}$ [47]. Analyzing CDRs for 2 million users, Hidalgo et al. found that persistent links tend to be reciprocal and associated with low degree nodes [48].

Miritello et al. analyzed CDRs for 20 million people and observed that individuals have a finite limit of number of active ties, and two different strategies for social communication [49, 50]. Sun et al. analyzed 20 million bus trips made by about 55% of the Singapore population and found distinct temporal patterns of regular encounters between strangers, resulting in a co-presence network across the entire metropolitan area [51].

3.2.3 Health and Public Safety

Using CDRs from the period of the 2008 earthquake in Rwanda, Kapoor et al. created a model for detection of the earthquake, the estimation of the epicenter, and determination of regions requiring relief efforts [52]. Aharony et al. performed and evaluated a fitness activity intervention with different reward schemes, based on face-to-face interactions [30], while Madan et al. studied how different illnesses (common cold, depression, anxiety) manifest themselves in common mobile-sensed features (WiFi, location, Bluetooth) and the effect of social exposure on obesity [53]. Salathé et al. showed that disease models simulated on top of proximity data obtained from a high school are in good agreement with the level of absenteeism during an influenza season [54], and emphasize that contact data is required to design effective immunization strategies.

3.2.4 Influence and Information Spread

Chronis et al. [15] and Madan et al. [55] investigated how face-to-face interactions affect political opinions. Wang et al. reported on the spread of viruses in mobile networks; Bluetooth viruses can have a very slow growth but can spread over time to a large portion of the network, while MMS viruses can have an explosive growth but their spread is limited to sub-networks [56]. Aharony et al. analyzed the usage of mobile apps in relation to face-to-face interactions and found that more face-to-face interaction increases the number of common applications [30]. Using RFID for sensing face-to-face interactions, Isella et al. estimated the most probable vehicles for infection propagation [57]. Using a similar technique, however applied to 232 children and 10 teachers in a primary school, Stehle et al. described a strong age homophily in the interactions between children [58].

Bagrow et al. showed how CDR communications, in relation to entertainment events (e.g. concerts, sporting events) and emergencies (e.g. fires, storms, earthquakes), have two well-distinguishable patterns in human movement [59]. Karsai et al. analyzed CDR from six millions users and found that strong ties tend to constrain the information spread within localized groups of individuals [60].

Studies of Christakis and Fowler on the spread of obesity and smoking in networks [61, 62] prompted a lively debate on how homophily and influence are confounded. Lyons was critical toward the statistical methods used [63]. Stelich et al. discussed how friendship formation in a dynamic network based on homophily can be mistaken for influence [64], and Shalizi and Thomas showed examples of how homophily and influence can be confounded [5]. Finally, Aral et al. provided a generalized statistical framework for distinguishing peer-to-peer influence from homophily in dynamic networks [65].

3.2.5 Socioeconomics and Organizational Behavior

For employees in a real work environment, face-to-face contact and email communication can be used to predict job satisfaction and group work quality [33]. Having more diverse social connections is correlated with economic opportunities, as found in the study containing CDRs of over 65 million users [66]. A similar result was reported in a study of economic status and physical proximity, where a direct correlation between more social interaction diversity and better financial status was found [30]. Or, as shown in a study of Belgian users, language regions in a country can be identified based solely on CDRs [67].

3.3 Privacy

Data collected about human participants is sensitive and ensuring privacy of the participants is a fundamental requirement—even when participants may have limited understanding of the implications of data sharing [68, 69]. A significant amount of literature exists regarding the possible attacks that can be performed on personal data, such as unauthorized analysis [70] with a view to decoding daily routines [71] or friendships [41] of the participants. In *side channel information* attacks, data from public datasets (e.g. online social networks) are used to re-identify users [72–74]. Even connecting the different records of one user within the same system can compromise privacy [72]. Specific attacks are also possible in network data, as nodes can be identified based on the network structure and attributes of the neighbors [75, 76].

Various de-identification techniques can be applied to the data. *Personally Identifiable Information* (PII) is any information that can be used to identify an individual, such as name, address, social security number, date and place of birth, employment, education, or financial status. In order to avoid re-identification and consequent malicious usage of data, PII can be completely removed, hidden by aggregation, or transformed to be less identifiable, resulting in a trade-off between privacy and utility [77]. Substituting PII with the correspondent one-way hash allows removal of plaintext information and breaks the link to other datasets. This method, however, does not guarantee protection from re-identification [78–81]. *K*-anonymity is a technique of ensuring that it is not possible to distinguish any user from at least $k - 1$ other in the dataset [82]; studies have shown that this method often may be too

weak [71]. L -diversity [83] and t -closeness [84] have been proposed as extensions of k -anonymity with stronger guarantees.

Another approach to introducing privacy is based on perturbing the data by introducing noise, with the goal of producing privacy-preserving statistics [85–89]. *Homomorphic encryption*, on the other hand, can be used to perform computation directly on the encrypted data, thus eliminating the need of exposing any sensitive information [90–93]; this technique has been applied, for example, to vehicle positioning data [94] and medical records [95].

The flows of data—creation, copying, sharing—can be restricted. *Information Flow Control* solutions such as [96–98] attempt to regulate the flow of information in digital systems. *Auditing* implementations such as [99–101] track the data flow by generating usage logs. *Data Expiration* makes data inaccessible after a specific time, for example by self-destruction or by invalidating encryption keys [102–105]. *Watermarking* identifies records using hidden fingerprints, to allow traceability and identification of leaks [106–108].

4 Motivation

Here we describe our primary motivation for deploying the Copenhagen Networks Study, featuring deep and high-resolution data and a longitudinal approach.

4.1 Multiplexity

The majority of big data studies use datasets containing data from a single source, such as call detail records (CDRs) [3], RFID sensors [109], Bluetooth scanners [110], or online social networks activity [2]. Although, as we presented in the Related Work section, analyzing these datasets has led to some exciting findings, we may however not understand how much bias is introduced in such single-channel approaches, particularly in the case of highly interconnected data such as social networks.

We recognize two primary concerns related to the single-source approach: incomplete data and limitation with respect to an interdisciplinary approach. For social networks, we intuitively understand that people communicate on multiple channels: they call each other on the phone, meet face-to-face, or correspond through email. Observing only one channel may introduce bias that is difficult to estimate [10]. Ranjan et al. investigated in [111] how CDR datasets, containing samples dependent upon user activity and requiring user participation, may bias our understanding of human mobility. The authors used data activities as the ground truth; due to applications running in the background, sending and requesting data, smartphones exchange data with the network much more often than typical users make calls and without the need for their participation. Comparing the number of locations and significant locations [112], they found that the CDRs reveal only a small fraction of users' mobility, when compared with data activity. The identified home and work locations, which are considered the most important locations, did not, however, differ significantly when estimated using either of the three channels (voice, SMS, and data).

Domains of science operate primarily on different types of data. Across the sciences, researchers are interested in distinct questions and use very different methods. Similarly, as datasets are obtained from different populations and in different situations, it is difficult to cross-validate or combine findings. Moreover, the single-channel origin of the data can be a preventive factor in applying expertise from multiple domains. If we collect data from multiple channels in the same studies, on the same population, we can work together across field boundaries and draw on the different expertise and results generated by the studies and thereby achieve more robust insights.

Social networks are ‘multiplex’ in the sense that many different types of links may connect any pair of nodes. While recent work [113, 114] has begun to explore the topic, a coherent theory describing multiplex, weighted, and directed networks remains beyond the frontier of our current understanding.

4.2 Sampling

In many big data studies, data sampling is uneven. CDRs, for example, only provide data when users actively engage, by making or receiving a phone call or SMS. Users can also have different patterns of engagement with social networks, some checking and interacting several times a day, while others only do so once a week [115]. Further, CDRs are typically provided by a single provider who has a finite market share. If the market share is 20% of the population and you consider only links internal to your dataset, this translates to only 4% of the total number of links, assuming random network and random sampling [3]. Thus, while CDRs might be sufficient when analysing of mobility, it is not clear that CDRs are a useful basis for social network analysis. Such uneven, sparse sampling decreases the resolution of data available for analysis. Ensuring the highest possible quality of the data, and even sampling, is possible with primarily passive data gathering, focusing on digital traces left by participants as they go through their lives, for example by using phones to automatically measure Bluetooth proximity, record location, and visible WiFi networks [8, 28, 30]. In cases where we cannot observe participants passively or when something simply goes wrong with the data collection, we aim to use the redundancy in the channels: if the participant turns off Bluetooth for a period, we can still estimate the proximity of participants using WiFi scans (as described in the Results section).

Uneven sampling not only reduces the quality of available data, but also—maybe more importantly—may lead to selection bias when choosing participants to include in the analysis. As investigated in [111], when only high-frequency voice-callers are chosen from a CDR dataset for the purpose of analysis, this can incur biases in Shannon entropy values (measure of uncertainty) of mobility, causing overestimation of the randomness of participants' behavior. Similarly, as shown in [115], choosing users with a large network and many interactions on Facebook may lead to overestimation of diversity in the ego-networks. Every time we have to discard a significant number of participants, we risk introducing bias in the data. Highly uneven sampling that cannot be corrected with redundant data, compels the researcher to make mostly arbitrary choices as part of the analysis, complicating subsequent analysis, especially when no well-established ground truth is available to understand the bias. Our goal here is to collect evenly sampled high-quality data for all the participants, so we do not have to discard anyone; an impossible goal, but one worth pursuing.

Since we only record data from a finite number of participants, our study population is also a subset, and every network we analyze will be sampled in some way, see [116] for a review on sampling. While the 2013 deployment produces a dataset that is nearly complete in terms of communication between the participants, it is clear that it is subject to other sampling-related issues. For example, a relatively small network embedded in a larger society has a large 'surface' of links pointing to the outside world, creating a *boundary specification problem* [117].

4.3 Dynamics

The networks and behaviors we observe are not static; rather they display dynamics on multiple time-scales. Long-term dynamics may be lost in big data studies when the participants are not followed for a sufficiently long period, and only a relatively narrow slice of data is acquired. Short-term dynamics may be missed when the sampling frequency is too low.

It is a well-established fact that social networks evolve over time [7, 118]. The time scale of the changes varies and depends on many factors, for example the semester cycle in students' life, changing schools or work, or simply getting older. Without following such dynamics, and if we focus on a single temporal slice, we risk missing an important aspect of human nature. To capture it, we need long-term studies, that follow participants for months or even years.

Our behavior is not static, even when measured for very short intervals. We have daily routines, meeting with different people in the morning and hanging out with other people in the evening, see Figure 4. Our workdays may see us going to places and interacting with people differently than on

weekends. It is easy to miss dynamics like these when the quality of the data is insufficient, either because it has not been sampled frequently enough or because of poor resolution, requiring large time bins.

Because each node has a limited bandwidth, only a small fraction of the network is actually ‘on’ at any given time, even if the underlying social network is very dense. Thus, to get from node A to node B, a piece of information may only travel on links that are active at subsequent times. Some progress has been made on the understanding of dynamic networks, for a recent review see [119]. However, in order to understand the dynamics of our highly dense, multiplex network, we need to expand and adapt the current methodologies, for example by adapting the link-based viewpoint to dynamical systems.

4.4 Feedback

In many studies, the data collection phase is separated from the analysis. The data might have been collected during usual operation, before the idea of the study had even been conceived (e.g. CDRs, WiFi logs), or access to the data might have not been granted before a single frozen and de-identified dataset was produced.

One real strength of the research proposed here is that, in addition to the richness of the collected data, we are able to run controlled experiments, including surveys distributed via the smartphone software. We can, for example, divide participants into sub-populations and expose them to distinct stimuli, addressing the topic of causality as well as confounding factors both of which have proven problematic [63, 120] for the current state-of-the-art [121, 122].

Moreover, we monitor the data quality not only on the most basic level of a participant (number of data points) but also by looking at the entire live dataset to understand if the quality of the collected data is sufficient to answer our research questions. This allows us to see and fix bugs in the data collection software, or learn that certain behaviors of the participants may introduce bias in the data: for example after discovering missing data, some interviewed students reported turning their phones off for the night to preserve battery. This allowed us to understand that, even if in terms of the raw numbers, we may be missing some hours of data per day for these specific participants, there was very little information in that particular data anyway.

Building systems with real-time data processing and access allows us to provide the participants with applications and services. It is an important part of the study not only to collect and analyze the data but also to learn how to create a feedback loop, directly feeding back extracted knowledge on behavior and interactions to the participants. We are interested in studying how personal data can be used to provide feedback about individual behavior and promote self-awareness and positive behavior change, which is an active area of research in Personal Informatics [123]. Applications for participants create value, which may be sufficient to allow us to deploy studies without buying a large number of smartphones to provide to participants. Our initial approach has included the development and deployment of a mobile app that provides feedback about personal mobility and social interactions based on personal participant data [124]. Preliminary results from the deployment of the app, participant surveys, and usage logs suggest an interest in such applications, with a subset of participants repeatedly using the mobile app for personal feedback [125]. It is clear that feedback can potentially influence the study results: awareness of a certain behavior may cause participants to want to change that behavior. We believe, however, that such feedback is unavoidable in any study, and studying the effects of such feedback (in order to account for it) is an active part of our research.

4.5 New Science

The ability to record the highly dynamic networks opens up a new, microscopic level of observation for the study of diffusion on the network. We are now able to study diffusion of behavior, such as expressions of happiness, academic performance, alcohol and other substance abuse, information, as well as real

world infectious disease (e.g. influenza). Some of these vectors may spread on some types of links, but not others. For example, influenza depends on physical proximity for its spread, while information may diffuse on all types of links; with the deep data approach we can study differences and similarities between various types of spreading and the interplay between the various communication channels [126, 127].

A crucial step when studying the structure and dynamics of networks is to identify communities (densely connected groups of nodes) [128, 129]. In social networks, communities roughly correspond to social spheres. Recently, we pointed out that communities in many real world networks display *pervasive overlap*, where each and every node belongs to more than one group [130]. It is important to underscore that the question of whether or not communities in networks exhibit pervasive overlap has great practical importance. For example, the patterns of epidemic spreading change, and the optimal corresponding societal countermeasures are very different, depending on the details of the network structure.

Although algorithms that detect disjoint communities have operated successfully since the notion of graph partitioning was introduced in the 1970s [131], we point out that most networks investigated so far are highly incomplete in multiple senses. Moreover, we can use a simple model to show that sampling could cause pervasively overlapping communities to appear to be disjoint [132]. The results reveal a fundamental problem related to working with incomplete data: *Without an accurate model of the structural ordering of the full network, we cannot estimate the implications of working with incomplete data.* Needless to say, this fact is of particular importance to studies carried out on (thin) slices of data, describing only a single communication channel, or a fraction of nodes using that channel. By creating a high-quality, high-resolution data set, we are able to form accurate descriptions of the full data set needed to inform a proper theory for incomplete data. A deeper understanding of sampling is instrumental for unleashing the full potential of data from the billions of mobile phones in use today.

5 Methods: Data Collection

The Copenhagen Networks Study aims to address the problem of single-modality data by collecting information from a number of sources that can be used to build networks, study social phenomena, and provide context necessary to interpret the findings. A series of questionnaires provides information on the socioeconomic background, psychological traces, and well-being of the participants; Facebook data enables us to learn about the presence and activity of subjects in the biggest online social networking platform [133]; finally, the smartphones carried by all participants record their location, telecommunication patterns, and face-to-face interactions. Sensor data is collected with fixed intervals, regardless of the users' activity, and thus the uneven sampling issue, daunting especially CDR-based studies, is mainly overcome. Finally, the study is performed on the largest and the most dense population to date in this type of studies. The physical density of the participants helps to address the problem of missing data, but raises new questions regarding privacy, since missing data about a person can, in many cases, be inferred from existing data of other participants. For example, if we know that person *A*, *B*, and *C* met at a certain location based on the data from person *A*, we do not need social and location data from *B* and *C* to know where and with whom they were spending time.

Below we describe the technical challenges and solutions in multi-channel data collection in 2012 and 2013 deployments. Data collection, anonymization, and storage were approved by the Danish Data Protection Agency, and comply with both local and EU regulations.

5.1 Data Sources

The data collected in the two studies were obtained from questionnaires, Facebook, mobile sensing, an anthropological field study, and the WiFi system on campus.

5.1.1 Questionnaires

In 2012 we deployed a survey containing 95 questions, covering socioeconomic factors, participants' working habits, and the Big Five Inventory (BFI) measuring personality traits [134]. The questions were presented as a Google Form and participation in the survey was optional.

In 2013 we posed 310 questions to each participant. These questions were prepared by a group of collaborating public health researchers, psychologists, anthropologists, and economists from the Social Fabric project (see Acknowledgements). The questions in the 2013 deployment included BFI, Rosenberg Self Esteem Scale [135], Narcissism NAR-Q [136], Satisfaction With Life Scale [137], Rotter's Locus of Control Scale [138], UCLA Loneliness scale [139], Self-efficacy [140], Cohen's perceived stress scale [141], Major Depression Inventory [142], The Copenhagen Social Relation Questionnaire [143], and Panas [144], as well as number of general health- and behavior-related questions. The questions were presented using a custom-built web application, which allowed for full customization and complete control over privacy and handling of the respondents' data. The questionnaire application is capable of presenting different types of questions, with branching depending on the answers given by the participant, and saving each participant's progress. The application is available as an open source project at github.com/MIT-Model-Open-Data-and-Identity-System/SensibleDTUData-Apps-Questionnaires. Participation in the survey was required for taking part in the experiment. In order to track and analyze temporal development, the survey (in a slightly modified form) was repeated every semester on all participating students.

5.1.2 Facebook Data

For all participants in both the 2012 and 2013 deployment, it was optional to authorize data collection from Facebook, and a large majority opted in. In the 2012 deployment, only the friendship graph was collected every 24 hours, until the original tokens expired. In the 2013 deployment, data from Facebook was collected as a snapshot, every 24 hours. The accessed scopes were birthday, education, feed, friend lists, friend requests, friends, groups, hometown, interests, likes, location, political views, religion, statuses, and work. We used long-lived Facebook access tokens, valid for 60 days, and when the tokens expired, participants received notification on their phones, prompting them to renew the authorizations. For the academic study purposes, the Facebook data provided rich demographics describing the participants, their structural (friendship graph) and functional (interactions) networks, as well as location updates.

5.1.3 Sensor Data

For the data collection from mobile phones, we used a modified version of the Funf framework [30] in both deployments. The data collection app was built using the framework runs on Android smartphones, which were handed out to participants (Samsung Galaxy Nexus in 2012 and LG Nexus 4 in 2013). All the bugfixes and the improvement of the framework are public and available under the OpenSensing github organization at github.com/organizations/OpenSensing.

In the 2012 deployment, we manually kept track of which phone was used by each student, and identified data using device IMEI numbers, but this created problems when the phones were returned and then handed out to other participants. Thus, in the 2013 deployment, the phones were registered in the system by the students in an OAuth2 authorization flow initiated from the phone; the data were identified by a token stored on the phone and embedded in the data files. The sensed data were saved as locally encrypted sqlite3 databases and then uploaded to the server every 2 hours, provided the phone was connected to WiFi. Each file contained 1 hour of participant data from all probes, saved as a single table. When uploaded, the data was decrypted, extracted, and included in the main study database.

5.1.4 Qualitative Data

An anthropological field study was included in the 2013 deployment. An anthropologist from the Social Fabric project was embedded within a randomly selected group of approximately 60 students (August 2013 – august 2014). A field study consists of participant observation within the selected group, collecting qualitative data while simultaneously engaging in the group activities. The goal is to collect data on various rationales underlying different group formations, while at the same time experiencing bodily and emotionally what it was like to be part of these formations [145]. The participant observation included all the student activities and courses, including extracurricular activities such as group work, parties, trips, and other social leisure activities. All participants were informed and periodically reminded about the role of the anthropologist.

In addition to its central purpose, the anthropological data adds to the multitude of different data channels, deepening the total pool of data. This proved useful for running and optimizing the project in a number of ways.

Firstly, data from qualitative social analysis are useful—in a very practical sense—in terms of acquiring feedback from the participants. One of the goals of the project is to provide value to the participants; in addition to providing quantified-self style access to data, we have also created a number of public services: a homepage, a Facebook page, and a blog, where news and information about the project can be posted and commented on. These services are intended to keep the students interested, as well as to make participants aware of the types and amounts of data collected (see Privacy section). Because of the anthropologist’s real-world engagement with the students, the qualitative feedback contains complex information about participants’ interests and opinions, including what annoyed, humored, or bored them. This input has been used to improve existing services, such as visualizations (content and visual expression), and to develop ideas for the future services. In summary, qualitative insights helped us understand the participants better and, in turn, to maintain and increase participation.

Secondly, the inclusion of qualitative data increases the potential for interdisciplinary work between the fields of computer science and social science. Our central goal is to capture the full richness of social interactions by increasing the number of recorded communication channels. Adding a qualitative social network approach makes it possible to relate the qualitative observations to the quantitative data obtained from the mobile sensing, creating an interdisciplinary space for methods and theory. We are particularly interested in the relationship between the observations made by the embedded anthropologist and the data recorded using questionnaires and mobile sensing, to answer questions about the elements difficult to capture using our high-resolution approach. Similarly, from the perspective of social sciences, we are able to consider what may be captured by incorporating quantitative data from mobile sensing into a qualitative data pool—and what can we learn about social networks using modern sensing technology.

Finally, these qualitative data can be used to ground the mathematical modeling process. Certain things are difficult or impossible to infer from quantitative measurements and mathematical models of social networks, particularly in regard to understanding *why* things happen in the network, as computational models tend to focus on *how*. Questions about relationship-links severing, tight networks dissolving, and who or what caused the break, can be very difficult to answer, but they are important with regard to understanding the dynamics of the social network. By including data concerned with answering *why* in social networks, we add a new level of understanding to the quantitative data.

5.1.5 WiFi Data

For the 2012 deployment, between August 2012 and May 2013, we were granted access to the campus WiFi system logs. Every 10 minutes the system provided metadata about all devices connected to the wireless access points on campus (access point MAC address and building location), together with the student ID used for authentication. We collected the data in a de-identified form, removing the student IDs and matching the participants with students in our study. Campus WiFi data was not collected for

the 2013 deployment.

5.2 Backend System

The backend system, used for data collection, storage, and access, was developed separately for the 2012 and 2013 deployments. The system developed in 2012 was not designed for extensibility, as it focused mostly on testing various solutions and approaches to massive sensor-driven data collection. Building on this experience, the system for the 2013 deployment was designed and implemented as an extensible framework for data collection, sharing, and analysis.

5.2.1 The 2012 Deployment

The system for the 2012 deployment was built as a Django web application. The data from the participants from the multiple sources, were stored in a CouchDB database. The informed consent was obtained by presenting a document to the participants after they authenticated with university credentials. The mobile sensing data was stored in multiple databases inside a single CouchDB instance and made available via an API. Participants could access their own data, using their university credentials. Although sufficient for the data collection and research access, the system performance was not adequate for exposing the data for real-time application access, mainly due to the inefficient de-identification scheme and insufficient database structure optimization.

5.2.2 The 2013 Deployment

The 2013 system was built as an open Personal Data System (openPDS) [146] in an extensible fashion. The architecture of the system is depicted in Figure 1 and consisted of three layers: platform, services, and applications. In the platform layer, the components common for multiple services were grouped, involving identity provider and participant-facing portal for granting authorizations. The identity provider was based on OpenID 2.0 standard and enabled single sign-on (SSO) for multiple applications. The authorizations were realized using OAuth2 and could be used with both web and mobile applications. Participants enroll into studies by giving informed consent and subsequently authorizing application to submit and access data from the study. The data storage was implemented using MongoDB. Participants can see the status and change their authorizations on the portal site, the system included an implementation of the Living Informed Consent [148].

5.3 Deployment Methods

Organizing studies of this size is a major undertaking. All parts from planning to execution have to be synchronized, and below we share some considerations and our approaches. While their main purpose was identical, the two deployments differed greatly in size and therefore also in the methods applied for enrolling and engaging the participants.

5.3.1 SensibleDTU 2012

In 2012 approximately 1,400 new students were admitted to the university, divided between two main branches of undergraduate programs. We focused our efforts on the larger branch containing 900 students, subdivided into 15 study lines (majors). For this deployment we had ~ 200 phones available to distribute between the students. To achieve maximal coverage and density of the social connections, we decided to only hand out phones in a few selected majors that had a sufficient number of students interested in participating in the experiment. Directly asking students about their interest in the study was not a good approach, as it could lead to biased estimates and would not scale well for a large number of individuals. Instead, we appealed to the competitive element of human nature by staging a competition,

running for two weeks from the start of the semester. All students had access to a web forum, which was kept separate for each major, where they could post ideas that could be realized by the data we would collect, and subsequently vote for their own ideas or three seed ideas that we provided. The goal of the competition was twofold; first we wanted students to register with their Facebook account, thereby enabling us to study their online social network, and second we wanted to see which major could gain most support (percentage of active students) behind a single idea. Students were informed about the project and competition by the Dean in person and at one of 15 talks given—one at each major. Students were told that our choice of participants would be based on the support each major could muster behind their strongest idea before a given deadline. This resulted in 24 new research ideas and 1026 unique votes. Four majors gained >93% support for at least one idea and were chosen to participate in the experiment.

The physical handing out of the phones was split into four major sessions, in which students from the chosen majors were invited; additional small sessions were arranged for students that were unable to attend the main ones. At each session, participants were introduced to our data collection methods, de-identification schemes, and were presented with the informed consent form. In addition, the participants were instructed to fill out the questionnaire. A small symbolic deposit in cash was requested from each student; this served partially as compensation for broken phones, but was mainly intended to encourage participants take better care of the phones, than if they had received them for free [147]. Upon receiving a phone, participants were instructed to install the data collector application. The configuration on each phone was manually checked when participants were leaving—this was particularly important to ensure high quality of data.

This approach had certain drawbacks; coding and setting up the web fora, manually visiting all majors and introducing them to the project and competition, and organizing the handout sessions required considerable effort and time. However, certain aspects were facilitated with strong support from the central administration of the university. A strong disadvantage of the outlined handout process is that phones were handed out 3-4 weeks into the semester, thus missing the very first interactions between students.

5.3.2 SensibleDTU 2013

The 2013 deployment was one order of magnitude larger, with 1000 phones to distribute. Furthermore, our focus shifted to engaging the students as early as possible. Pamphlets informing prospective undergraduate students about the project were sent out along with the official acceptance letters from the university. Early-birds who registered online via Facebook using the links given in the pamphlet were promised phones before the start of their studies. Students from both branches of undergraduate programs were invited to participate (approximately 1500 individuals in total), as we expected an adoption percentage between 30% and 60%. Around 300 phones were handed out to early-birds, and an additional 200 were handed out during the first weeks of semester. As the adoption rate plateaued, we invited undergraduate students from older years to participate in the project.

The structure of the physical handout was also modified, the participants were requested to enroll online before receiving the phone. Moreover, the informed consent and the questionnaire were part of the registration. Again, we required a symbolic cash deposit for each phone. We pre-installed custom software on each phone to streamline the handout process; students still had to finalize set up of the phones (make them Bluetooth-discoverable, activate WiFi connection, etc.).

For researchers considering similar projects with large scale handouts, we recommend that the pool of subjects are engaged in the projects as early as possible and be sure to keep their interest. Make it easy for participants to contact you, preferably through media platforms aimed at their specific age group. Establish clear procedures in case of malfunctions. On a side note, if collecting even a small deposit, when multiplied by a factor of 1000, the total can add up to significant amount, which must be handled properly.

6 Methods: Privacy

When collecting data of very high resolution, over an extended period, from a large population, it is crucial to address the privacy of the participants appropriately. We measure the privacy as a difference between what a participant understands and consents to regarding her data, and what in fact happens to these data.

We believe that ensuring sufficient privacy for the participants, in large part, is the task of providing them with tools to align the data usage with their understanding. Such privacy tools must be of two kinds: to inform, ensuring participants understand the situation, and to control, aligning the situation with the participant’s preferences. There is a tight loop where these tools interact: as the participant grows more informed, she may decide to change the settings, and then verify if the change had the expected result. By exercising the right to information and control, the participant expresses Living Informed Consent as described in [148].

Not all students are interested in privacy, in fact we experienced quite the opposite attitude. During our current deployments the questions regarding privacy were rarely asked by the participants, as they tended to accept any terms presented to them without thorough analysis. It is our—the researchers’—responsibility to make the participants more aware and empowered to make the right decisions regarding their privacy: by providing the tools, promoting their usage, and engaging in a dialog about privacy-related issues.

In the 2012 deployment, we used a basic informed consent procedure with an online form accepted by the participants, after they authenticated with the university account system. The accepted form was then stored in a database, together with the username, timestamp, and the full text displayed to the participant. The form itself was a text in Danish, describing the study purpose, parties responsible, and participants’ rights and obligations. The full text is available at [149] with English translation available at [150].

In the 2013 deployment, we used our backend solution (described in Section Backend System) to address the informed consent procedure and privacy in general. The account system, realized as an OpenID 2.0 server, allowed us to enroll participants, while also supporting research and developer accounts (with different levels of data access). The sensitive Personally Identifiable Information attributes (PIIs) of the participants were kept completely separate from the participant data, all the applications identified participants based only on the pseudonym identifiers. The applications could also access a controlled set of identity attributes for the purpose of personalization (e.g. greeting the participant by name), subject to user OAuth2 authorization. In the enrollment into the study, after the participant had accepted the informed consent document—essentially identical to that from 2012 deployment—a token for a scope *enroll* was created and shared between the platform and service (see Figure 1). The acceptance of the document was recorded in the database by storing the username, timestamp, hash of the text presented to the participant, as well as the git commit identifying the version of the form.

All the communication in the system was realized over HTTPS, and endpoints were protected with short-lived OAuth2 bearer tokens. The text of the documents, including informed consent, was stored in a git repository, allowing us to modify everything, while still maintaining the history and being able to reference which version each participant has seen and accepted. A single page overview of the status of the authorizations, presented in Figure 2, is an important step in moving beyond lengthy, incomprehensible legal documents accepted by the users blindly and giving more control over permissions to the participant.

In the 2013 deployment, the participants could access all their data using the same API as the one provided for the researchers and application developers. To simplify the navigation, we developed a data viewer application as depicted in Figure 3, which supports building queries with all the basic parameters in a more user-friendly way than constructing API URLs. Simply having access to all the raw data is, however, not sufficient, as it is really high-level inferences drawn from the data that are important to understand, for example *Is someone accessing my data to see how fast I drive or to study population mobility?* For this purpose, we promoted the development of a *question & answer* framework, where the

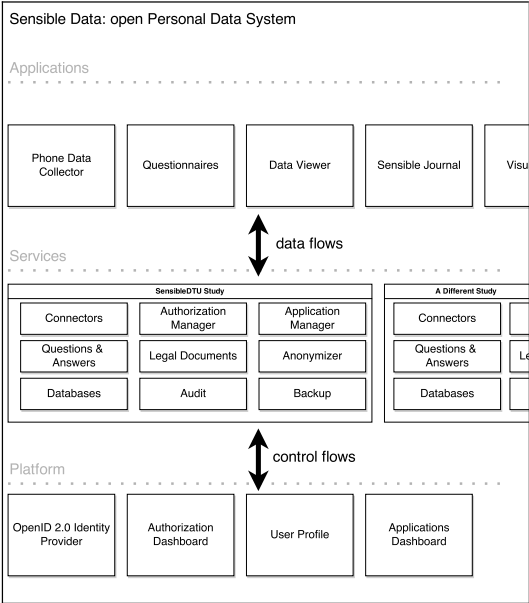


Figure 1. Sensible Data openPDS architecture. This system is used in the 2013 deployment and consists of three layers: platform, services, and applications. The platform contains element common for multiple services (in this context: studies). The studies are the deployments of particular data collection efforts. The applications are OAuth2 clients to studies and can submit and access data, based on user authorizations.

high-level features are extracted from the data before leaving the server, promoting better participant understanding of data flows. This is aligned with the vision of the open Personal Data Store [146].

Finally, for the purposes of engaging the participants in the discussion about privacy, we published blogposts (e.g. <https://www.sensible.dtu.dk/?p=1622>), presented relevant material to students, and answered their questions via the Facebook page(<https://www.facebook.com/SensibleDtu>).

7 Results

As described in the previous sections, our study has collected comprehensive data about a number of aspects regarding human behavior. Below, we discuss primary data channels and report some early results and findings. The results are mainly based on the 2012 deployment due to the availability of longitudinal data.

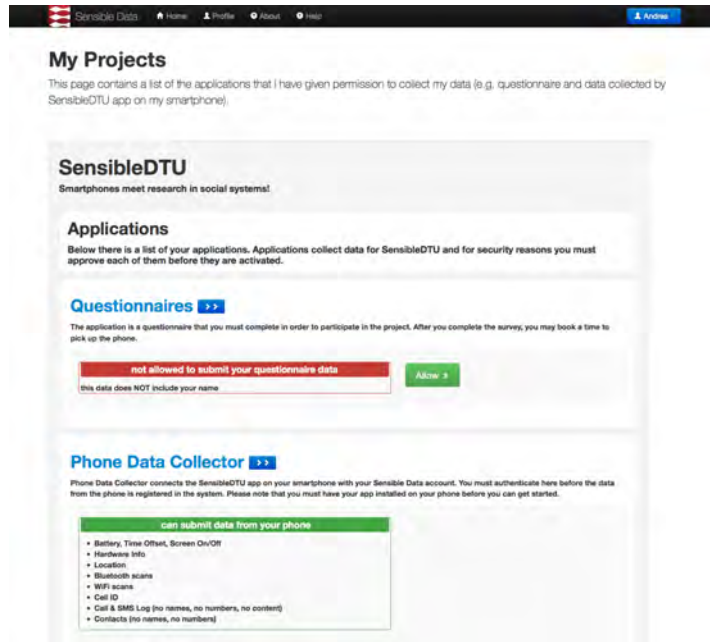


Figure 2. Authorizations page. Participants have an overview of the studies in which they are enrolled and which applications are able to submit to and access their data. This is an important step towards users’ understanding what happens with their data and to exercising control over it. This figure shows a translated version of the original page that participants saw in Danish.

7.1 Bluetooth and Social Ties

Bluetooth is a wireless technology ubiquitous in modern-day mobile devices. It is used for short-range communication between devices, including smartphones, hands-free headsets, tablets, and other wearables. As the transmitters used in mobile devices are primarily of very short range—between 5 and 10 m (16 – 33 feet)—detection of the devices of other participants (set in ‘visible’ mode) can be used as a proxy for face-to-face interactions [28]. We take the individual Bluetooth scans in the form (i, j, t, σ) , denoting that device i has observed device j at time t with signal strength σ . Bluetooth scans do not constitute a perfect proxy for face-to-face interactions [151], since a) it is possible for people within 10 m radius not to interact socially, and b) it is possible to interact socially over a distance greater than 10 m , nevertheless, they have been successfully used for sensing social networks [30] or crowd tracking [152].

Between October 1st, 2012 and September 1st, 2013, we collected 12 623 599 Bluetooth observations in which we observed 153 208 unique devices. The scans on the participants’ phones were triggered every five minutes, measured from the last time the phone was powered on. Thus, the phones scanned for Bluetooth in a desynchronized fashion, and not according to a global schedule. To account for this, when extracting

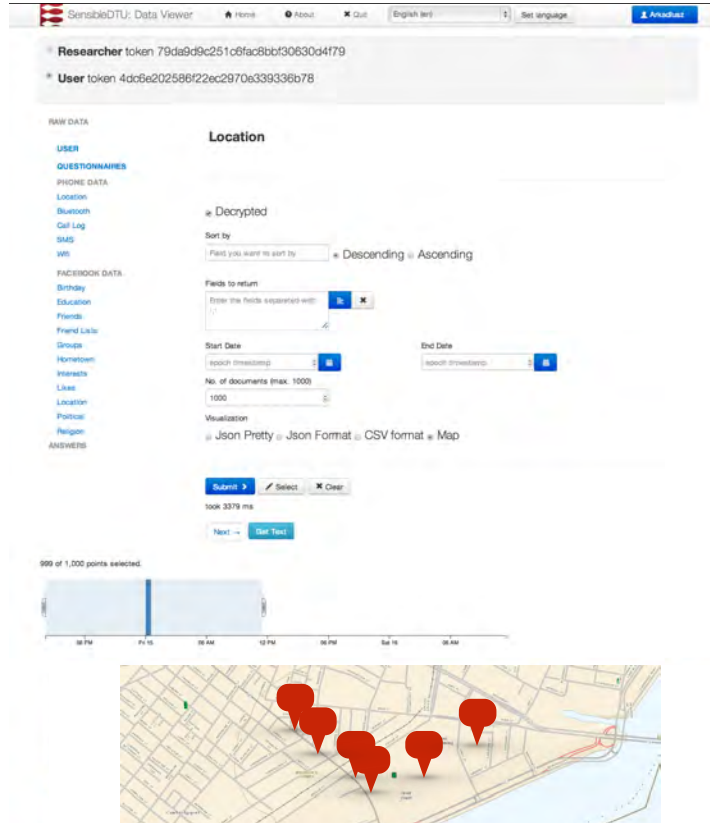


Figure 3. Data viewer application. All the collected data can be explored and accessed via an API. The API is the same for research, application, and end-user access, the endpoints are protected by OAuth2 bearer token. Map image from USGS National Map Viewer, replacing original image used in the deployed application (Google Maps).

interactions from the raw Bluetooth scans, we bin them into fixed-length time windows, aggregating the scans within them. The resulting adjacency matrix, $W_{\Delta t}$ does not have to be strictly symmetric, meaning that participant i can observe participant j in time-bin t , but not the other way around. Here we assume that Bluetooth scans do not produce false positives (devices are not discovered unless they are really there), and in the subsequent network analysis, we force the matrix to be symmetric, assuming that if participant i observed participant j , the opposite is also true.

The interactions between the participants exhibit both daily and weekly rhythms. Figure 4 shows

that the topology of the network of face-to-face meetings changes significantly within single day, revealing academic and social patterns formed by the students. Similarly, the intensity of the interactions varies during the week, see Figure 5.

Aggregating over large time-windows blurs the social interactions (network is close to fully connected) while a narrow window reveals detailed temporal structures in the network. Figure 6a shows the aggregated degree distributions for varying temporal resolutions, with $P(k)$ being shifted towards higher degrees for larger window sizes; this is an expected behavior pattern since each node has more time to amass connections. Figure 6b presents the opposite effect, where the edge weight distributions $P(w)$ shift towards lower weights for larger windows; this is a consequence on definition of a link for longer time-scales or, conversely, of links appearing in each window on shorter timescales. To compare the distribution between timescales, we rescale the properties according to Krings et al. [153] as $Q(x) = \langle x \rangle P(x / \langle x \rangle)$ with $\langle x \rangle = \sum x P(x)$ (Figure 6c and 6d). The divergence of the rescaled distributions suggest a difference in underlying social dynamics between long and short timescales, an observation supported by recent work on temporal networks [43, 153, 154].

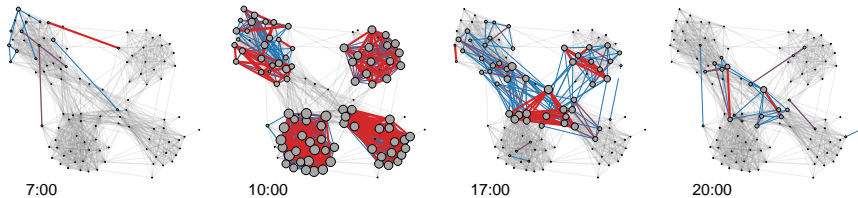


Figure 4. Dynamics of face-to-face interactions in the 2012 deployment. The participants meet in the morning, attend classes within four different study lines, and interact across majors in the evening. Edges are colored according to the frequency of observation, ranging from low (blue) to high (red). With 24 possible observations per hour, the color thresholds are respectively: blue ($0 < \text{observations} \leq 6$), purple ($6 < \text{observations} \leq 12$), and red (< 12 observations). Node size is linearly scaled according to degree.

7.2 WiFi as an Additional Channel for Social Ties

Over the last two decades, wireless technology has transformed our society to the degree where every city in the developed world is now fully covered by mobile [155] and wireless networks [156]. The data collector application for mobile phones was configured to scan for wireless networks in constant intervals, but also to record the results of scans triggered by any other application running on the phone (‘opportunistic’ sensing). Out of the box, Android OS scans for WiFi every 15 seconds, and since we collected these data, our database contains 42 692 072 WiFi observations, with 142 871 unique networks (SSIDs) between October 1st, 2012 and September 1st, 2013 (i.e. the 2012 deployment). Below we present the preliminary result on WiFi as an additional data-stream for social ties, to provide an example of how our multiple layers of information can complement and enrich each other.

For computational social science, using Bluetooth-based detection of participants’ devices as a proxy for face-to-face interactions is a well-established method [18, 28, 30]. The usage of WiFi as a social proxy has been investigated [157], but, to our knowledge, has not yet been used in a large-scale longitudinal study. For the method we describe here, the participants’ devices do not sense each other, instead they record the visible beacons (in this instance WiFi access points) in their environment. Then, physical proximity between two devices—or lack thereof—can be inferred by comparing results of the WiFi scans

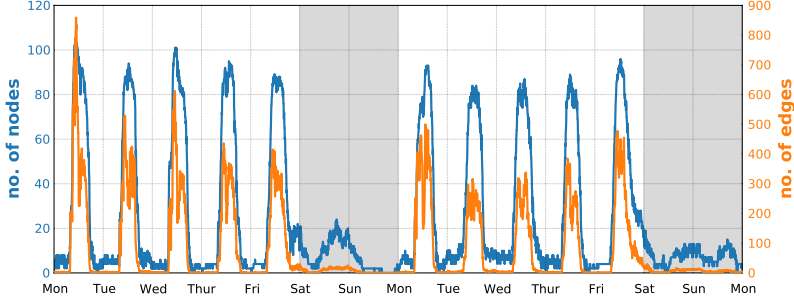


Figure 5. Weekly temporal dynamics of interactions. Face-to-face interaction patterns of participants in 5-minute time-bins over two weeks. Only active participants are included, i.e. those that have either observed another person or themselves been observed in a given time-bin. On average we observed 29 edges and 12 nodes in 5-minute time-bins and registered 10 634 unique links between participants.

that occurred within a sufficiently small time window. Proximity is assumed if the lists of access points (APs) visible to both devices are similar according to a similarity measure. We establish the appropriate definition of the similarity measure in a data-driven manner, based on best fit to Bluetooth data. The strategy is to compare the lists of results in 10-minute-long time bins, which corresponds to the forced sampling period of the WiFi probe as well as to our analysis of Bluetooth data. If there are multiple scans within the 10-minute bin, the results are compared pair-wise, and proximity is assumed if at least one of these comparisons is positive. The possibility of extracting face-to-face interactions from such signals is interesting, due to the ubiquitous nature of WiFi and high temporal resolution of the signal.

We consider four measures and present their performance in Figure 7. Figure 7a shows the positive predictive value and recall as a function of minimum number of overlapping access points ($|X \cap Y|$) required to assume physical proximity. In approximately 98% of all Bluetooth encounters, at least one access point was seen by both devices. However, the recall drops quickly with the increase of their required number. This measure favors interactions in places with a high number of access points, where it is more likely that devices will have a large scan overlap. The result confirms that lack of a common AP has a very high positive predictive power as a proxy for *lack* of physical proximity, as postulated in [158]. Note, that for the remaining measures, we assume at last one overlapping AP in the compared lists of scan results.

The overlap coefficient defined as $\text{overlap}(X, Y) = \frac{|X \cap Y|}{\min(|X|, |Y|)}$ penalizes encounters taking place in WiFi-dense areas, due to higher probability of one device picking up a signal from a remote access point that is not available to the other device, see Figure 7b.

Next, we compare the received signal strengths between overlapping routers using the mean ℓ_1 -norm (mean Manhattan distance, $\frac{\|X \cap Y\|_1}{|X \cap Y|}$). Received signal strength (RSSI) is measured in *dBm* and the Manhattan distance between two routers is the difference in the RSSI between them, measured in *dB*. Thus, the mean Manhattan distance is the mean difference in received signal strength of the overlapping routers in the two compared scans.

Finally, we investigate the similarity based on the router with the highest received signal strength—

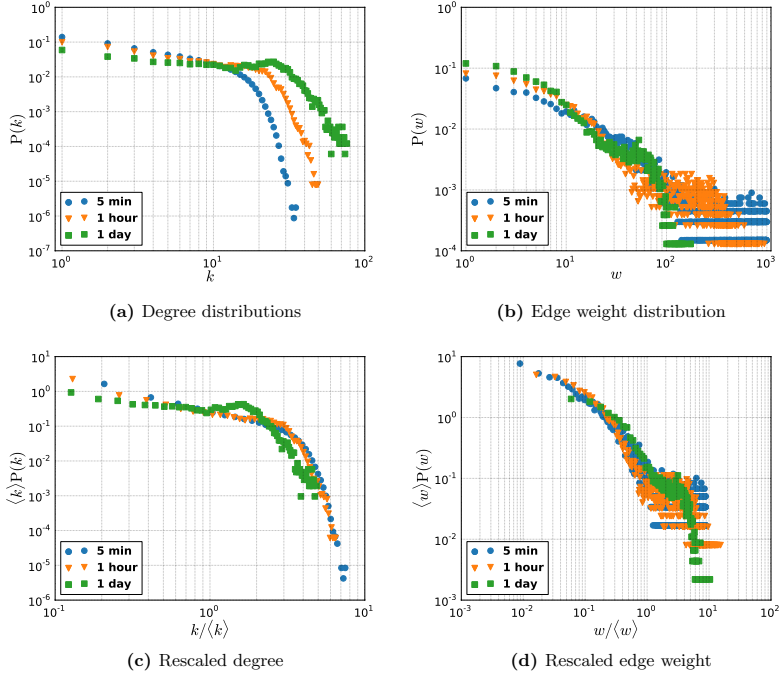


Figure 6. Face-to-face network properties at different resolution levels. Distributions are calculated by aggregating sub-distributions across temporal window. Differences in rescaled distributions suggest that social dynamics unfold on multiple timescales.

the proximity is assumed whenever it is the same access point for both devices, $\max(X) = \max(Y)$. This measure provides both high recall and positive predictive value and, after further investigation for the causes for errors, is a candidate proxy for face-to-face interactions.

The performance of face-to-face event detection based on WiFi can be further improved by applying machine-learning approaches [158, 159]. It is yet to be established, by using longitudinal data, whether the errors in using single features are caused by inherent noise in measuring the environment, or if there is a bias that could be quantified and mitigated. Most importantly, the present analysis is a proof-of-concept and further investigation is required to verify if networks inferred from WiFi and Bluetooth signals are satisfyingly similar, before WiFi can be used as an autonomous channel for face-to-face event detection in the context of current and future studies. Being able to quantify the performance of multi-channel approximation of face-to-face interaction and to apply it in the data analysis is crucial to address the problem of missing data, as well as to estimate the feasibility and understand the limitations of single-channel studies.

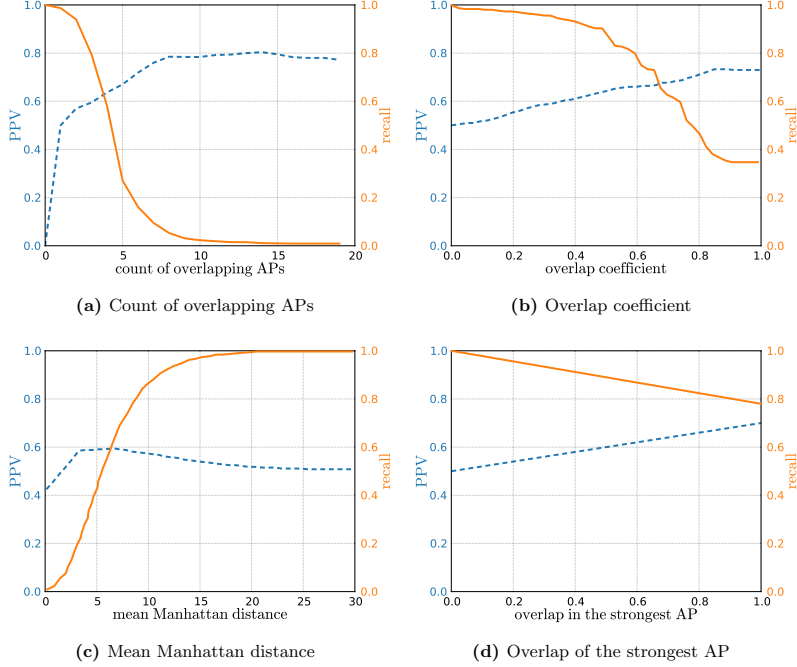


Figure 7. WiFi similarity measures. Positive predictive value (precision, ratio of number of true positives to number of positive calls, marked with dashed lines) and recall (sensitivity, fraction of retrieved positives, marked with solid lines) as functions of parameters in different similarity measures. In 98% of face-to-face meetings derived from Bluetooth, the two devices also sensed at least one common access point (a). Identical strongest access point for two separate mobile devices is a strong indication of a face-to-face meeting (d).

7.3 Location and Mobility

A number of applications ranging from urban planning, to traffic management, to containment of biological diseases rely on the ability to accurately predict human mobility. Mining location data allows extraction of semantic information such as points of interest, trajectories, and modes of transportation [160]. In this section we report the preliminary results of an exploratory data analysis of location and mobility patterns.

Location data was obtained by periodically collecting the best position estimate from the location sensor on each phone, as well as recording location updates triggered by other applications running on the phone (opportunistic behavior). In total we collected 7593134 data points in 2012 deployment in the form (userid, timestamp, latitude, longitude, accuracy). The best-effort nature of the data presents new challenges when compared with the majority of location mining literature, which focuses on high-

frequency, high-precision GPS data. Location samples on the smartphones can be generated by different providers, depending on the availability of the Android sensors, as explained in `developer.android.com/guide/topics/location/strategies.html`. For this reason, accuracy of the collected position can vary between a few meters for GPS locations, to hundreds of meters for cell tower location. Figure 8a shows the estimated cumulative distribution function for the accuracy of samples; almost 90% of the samples have a reported accuracy better than 40 meters.

We calculate the radius of gyration r_g as defined in [37] and approximate the probability distribution function using a gaussian kernel density estimation, see Figure 8b. We select the appropriate kernel bandwidth through leave-one-out cross-validation scheme from Statsmodels KDEMultivariate class [161]. The kernel density peaks around 10^2 km and then rapidly goes down, displaying a fat-tailed distribution. Manual inspection of the few participants with r_g around 10^3 km revealed that travels abroad can amount to such high mobility. Although we acknowledge that this density estimation suffers due to the low number of samples, our measurements suggest that real participant mobility is underestimated in studies based solely on CDRs, such as in [37], as they fail to capture travels outside of the covered area.

Figure 8c shows a two-dimensional histogram of the locations, with hexagonal binning and logarithmic color scale (from blue to red). The red hotspots identify the most active places, such as the university campus and dormitories. The white spots are the frequently visited areas, such as major streets and roads, stations, train lines, and the city center.

From the raw location data we can extract stop locations as groups of locations clustered within distance D and time T [162–165]. By drawing edges between stop locations for each participant, so that the most frequent transitions stand out, we can reveal patterns of collective mobility (Figure 8d).

7.4 Call & Text Communication Patterns

With the advent of mobile phones in the late 20th century, the way we communicate has changed dramatically. We are no longer restricted to landlines and are able to move around in physical space while communicating over long distances.

The ability to efficiently map communication networks and mobility patterns (using cell towers) for large populations has made it possible to quantify human mobility patterns, including investigations of social structure evolution [166], economic development [66], human mobility [36, 37], spreading patterns [56], and collective behavior with respect to emergencies [59]. In this study, we have collected call logs from each phone as (caller, callee, duration, timestamp, call type), where the call type could be incoming, outgoing, or missed. Text logs contained (sender, recipient, timestamp, incoming/outgoing, one-way hash of content).

In the 2012 deployment we collected 56 902 incoming and outgoing calls, of which 42 157 had a duration longer than zero seconds. The average duration of the calls was $\langle d \rangle = 142.04$ s, with a median duration of 48.0s. The average ratio between incoming and outgoing calls for a participant was $r_{in/out} = 0.98$. In the same period, we collected 161 591 text messages with the average ratio for a participant $r_{in/out} = 1.96$.

We find a Pearson correlation of 0.75 ($p \ll 0.05$) between the number of unique contacts participants contacted via SMS and voice calls, as depicted in Figure 9. However, the similarity $\sigma = |N_{call} \cap N_{text}| / |N_{call} \cup N_{text}|$ between the persons a participant contacts via calls (N_{call}) and SMS (N_{text}) is on average $\langle \sigma \rangle = 0.37$, suggesting that even though participants utilize both forms of communication in similar capacity, those two are, in fact, used for distinct purposes.

Figure 10 shows the communication for SMS and voice calls (both incoming and outgoing, between participants and with the external world) as a time series, calculated through the entire year and scaled to denote the mean count of interactions participants had in given hourly time-bins in the course of a week. Also here, we notice differences between the two channels. While both clearly show a decrease in activity during lunch time, call activity peaks around the end of the business day and drops until next morning. In contrast, after a similar decrease that we can associate with commute, SMS displays another evening peak. Also at night, SMS seems to be a more acceptable form of communication, with message

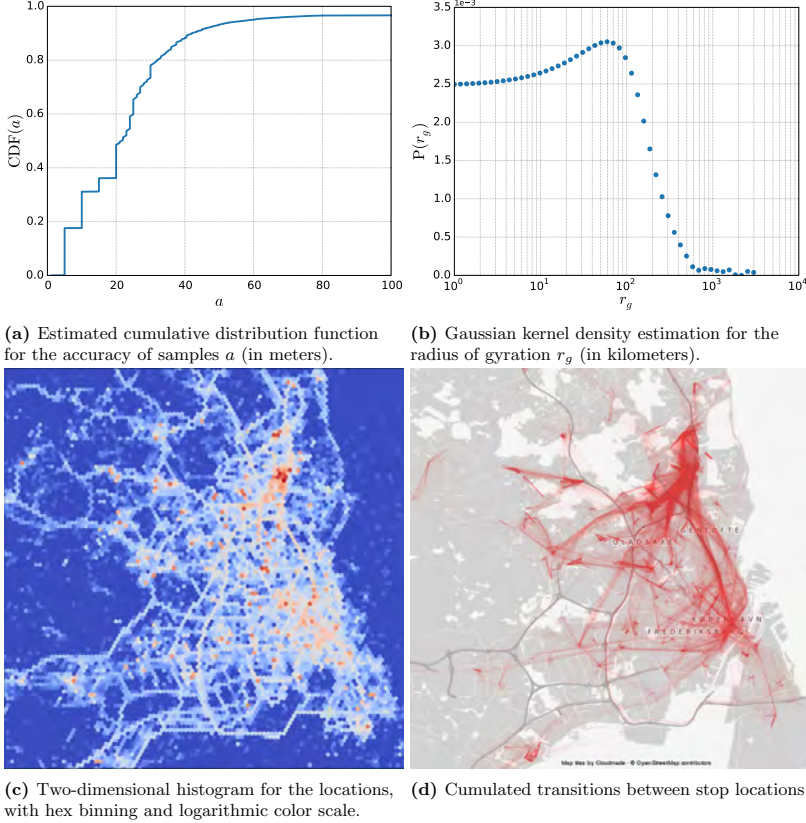


Figure 8. Location and Mobility. We show the accuracy of the collected samples, radius of gyration of the participants, and identify patterns of collective mobility.

exchanges continuing late and starting early, especially on Friday night, when the party never seems to stop.

We point out that the call and SMS dynamics display patterns that are quite distinct from face-to-face interactions between participants as seen in Figure 5. Although calls and SMS communication are different on the weekends, the difference is not as dramatic as in the face-to-face interactions between the participants. This indicates that the face-to-face interactions we observe during the week are driven primarily by university-related activities, and only few of these ties manifest themselves during the weekends, despite the fact that the participants are clearly socially active, sending and receiving calls and messages.

In Figure 11, we focus on a single day (Friday) and show activation of links between participants

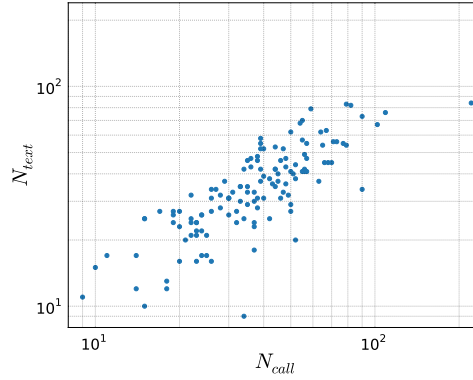


Figure 9. Diversity of communication logs. Diversity is estimated as the set of unique numbers that a person has contacted or been contacted by in the given time period on a given channel. We note a strong correlation in diversity (Pearson correlation of 0.75, $p \ll 0.05$), whereas the similarity of the sets of nodes is fairly low (on average $\langle \sigma \rangle = 0.37$).

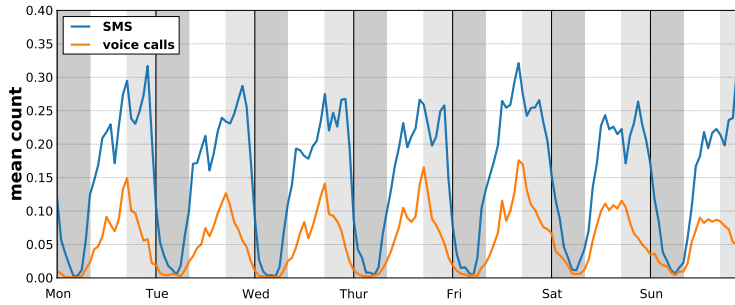


Figure 10. Weekly temporal dynamics of interactions. All calls and SMS, both incoming and outgoing, were calculated over the entire dataset and averaged per participant and per week, showing the mean number of interactions participants had in a given weekly bin. Light gray denotes 5pm, the time when lectures end at the university, dark gray covers night between 12 midnight and 8am. SMS is used more for communication outside regular business hours.

in three channels: voice calls, text messages, and face-to-face meetings. The three networks show very different views of the participants' social interactions.

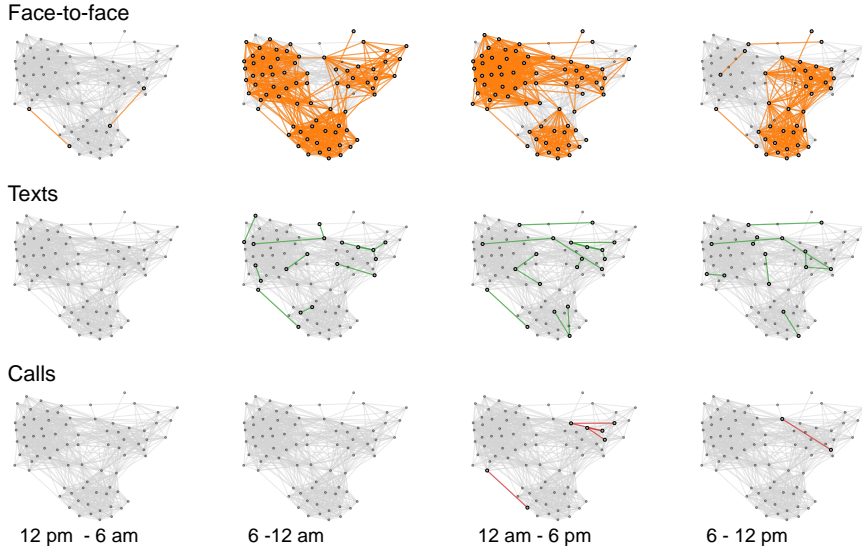


Figure 11. Daily activations in three networks. One day (Friday) in a network showing how different views are produced by observing different channels.

7.5 Online friendships

The past years have witnessed a shift in our interaction patterns, as we have adapted new forms of online communication. Facebook is to date the largest online social community with more than 1 billion users worldwide [167]. Collecting information about friendship ties and communication flows allows us to construct a comprehensive picture of the online persona. Combined with other recorded communication channels we have an unparalleled opportunity to piece together an almost complete picture of all major human communication channels. In the following section we consider Facebook data obtained from the 2013 deployment. In contrast to the first deployment, we also collected interaction data in this deployment. For a representative week (Oct. 14 - Oct. 21, 2013), we collected 155 interactions (edges) between 157 nodes, yielding an average degree $\langle d \rangle = 1.98$, average clustering $\langle c \rangle = 0.069$, and average shortest path in the giant component (86 nodes) $\langle l \rangle = 6.52$. The network is shown in the left-most panel of Figure 12. By comparing with other channels we can begin to understand how well online social networks correspond to real life meetings. The corresponding face-to-face network (orange) is shown in Figure 12, where weak links, i.e. edges with fewer than 147 observations (20%) are discarded. Corresponding statistics are for the 307 nodes and 3 217 active edges: $\langle d \rangle = 20.96$, $\langle c \rangle = 0.71$, and $\langle l \rangle = 3.2$. Irrespective of the large difference in edges, the online network still contains valuable information about social interactions that the face-to-face network misses—red edges in Figure 12.

A simple method for quantifying the similarity between two networks is to consider the fraction of links we can recover from them. Sorting face-to-face edges according to activity (highest first) we consider the

fraction of online ties the top k Bluetooth links correspond to. Figure 13a shows that 10% of the strongest Bluetooth ties account for more than 50% of the Facebook interactions. However, as noted before, the Bluetooth channel does not recover all online interactions—23.58% of Facebook ties are unaccounted for. Applying this measure between Bluetooth and voice calls (Figure 13b) shows a similar behavior, while there is low similarity between voice calls and Facebook ties (Figure 13c).



Figure 12. Face-to-face and online activity. The figure shows data from the 2013 deployment for one representative week. **Online:** Interactions (messages, wall posts, photos, etc.) between participants on Facebook. **Face-to-Face:** Only the most active edges, which account for 80% of all traffic, are shown for clarity. **Extra Info. F2F:** Extra information contained in the Bluetooth data shown as the difference in the set of edges. **Extra Info. Online:** Additional information contained in the Facebook data.

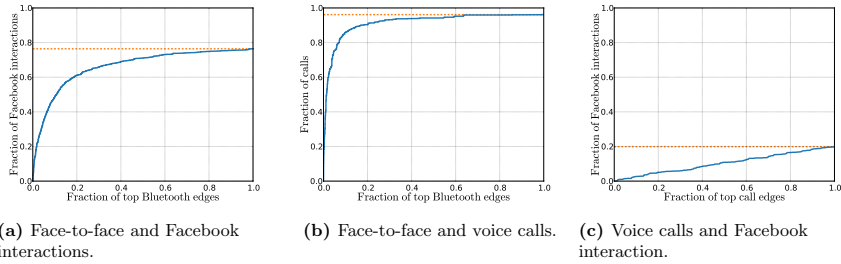


Figure 13. Network similarity. Defined as the fraction of ties from one communication channel that can be recovered by considering the top k fraction of edges from a different channel. Orange dashed line indicates the maximum fraction of ties the network accounts for. The strongest 10% of face-to-face interactions account for $> 50\%$ of online ties and $\sim 90\%$ of call ties, while 23.58% of Facebook ties and 3.85% of call ties are not contained in the Bluetooth data. Between call and Facebook, the 10% strongest call ties account for $< 3\%$ while in total $> 80\%$ of Facebook ties are unaccounted. All values are calculated for interactions that took place in January 2014.

7.6 Personality traits

While the data from mobile sensing and online social networks provide insights primarily into the structure of social ties, we are also interested in the demographics, psychological and health traits, and interests of the participants. Knowing these characteristics, we can start answering questions about the reasons for the observed network formation; why are ties created and what drives their dynamics? For example, homophily plays a vital role in how we establish, maintain, and destroy social ties [168].

Within the study, participants answered questions covering the aforementioned domains. These questions included the widely used *Big Five Inventory* [134] measuring five broad domains of human personality traits: openness, extraversion, neuroticism, agreeableness, and conscientiousness. The traits are scored on a 5-point Likert-type scale (low to high), and the average score of questions related to each personality domain are calculated. As Big Five has been collected for various populations, including a representative sample from Germany [169] and a representative sample covering students mixed with the general population from Western Europe [170], we report the results from the 2012 deployment in Figure 14, suggesting that our population is unbiased with respect to these important traits.

Following the idea that personality is correlated with the structure of the social networks, we examine how the Big Five Inventory traits relate to the communication ego networks of the participants: number of Facebook friends, amount of communication with these friends, number of people ever contacted over voice calls or SMS. We only consider communication within the study, in the 2013 deployment for $N=488$ participants for whom complete and longitudinal data was available. It is worth noting that participants answered the questions very early in the semester, and that we anecdotally know that a vast majority of the friendships observed between participants are ‘new’ in that they are between people who met when they started studying. Thus, we mainly observe the effect of personality on the network structure, not the other way around. The results are consistent with the literature, where Extraversion was shown to be correlated with number of Facebook friends [171]. Extending this result, Figure 15 depicts the correlation between Extraversion and number of Facebook friends (structural network) N_{fs} (Figure 15a), volume of interactions with these friends (functional network) N_{ff} (Figure 15b), number of friends contacted via voice calls N_c (Figure 15c), and number of friends contacted via SMS N_s (Figure 15d). In Table 15e, we show the (Pearson) correlation between all five traits and the aforementioned communication channels, reporting only significant results. The values of correlation for Extraversion are consistent across the networks, and are close to those reported in [171, 172] (~ 0.2). Following the result from Section Call & Text Communication Patterns, where we showed that the communication in SMS and call networks are similar in volume, however have limited overlap in terms of who participants contact, both those channels show similar correlation with Extraversion. Here, we only scratched the surface with regard to the relation between personality and behavioral data. The relation between different behavioral features, network structure, and personality has been studied in [173–176]. By showing the impact of Extraversion on the network formed with participants inside the study is consistent with values reported for general populations, we indicate that within the Copenhagen Networks Study, we capture a true social system, with different personalities positioned differently in the network.

8 Perspectives

We expect that the amount of data collected about human beings will continue to increase. New and better services will be offered to users, more effective advertising will be implemented, and researchers will learn more about human nature. As the complexity and scale of studies on social systems grows, collection of high-resolution data for studying human behavior will become increasingly challenging on multiple levels, even when offset by the technical advancements. Technical preparations, administrative tasks, and tracking data quality are a substantial effort for an entire team, before even considering the scientific work of data analysis. It is thus an important challenge for the scientific community to create

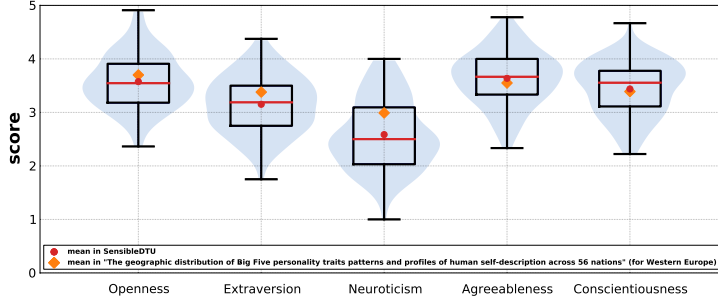


Figure 14. Personality traits. Violin plot of personality traits. Summary statistics are: **openness** $\mu_O = 3.58$, $\sigma_O = 0.52$; **extraversion** $\mu_E = 3.15$, $\sigma_E = 0.53$; **neuroticism** $\mu_N = 2.59$, $\sigma_N = 0.65$; **agreeableness** $\mu_A = 3.64$, $\sigma_A = 0.51$; **conscientiousness** $\mu_C = 3.44$, $\sigma_C = 0.51$. Mean values from our deployment (red circles) compared with mean values reported for Western Europe (mixed student and general population) [170] (orange diamonds).

and embrace re-usable solutions, including best practices in privacy policies and deployment procedures, supporting technologies for data collection, handling, and analysis methods.

The results presented in this paper—while still preliminary considering the intended multi-year span of the project—clearly reveal that a single stream of data rarely supplies a comprehensive picture of human interactions, behavior, or mobility. At the same time, creating larger studies, in terms of number of participants, duration, channels observed, or resolution, is becoming expensive using the current approach. The interest of the participants depends on the value they get in return and the inconvenience the study imposes on their lives. The inconvenience may be measured by decreased battery life of their phones, annoyance of answering questionnaires, and giving up some privacy. The value, on the other hand, is classically created by offering material incentives, such as paying participants or, as in our case, providing smartphones and creating services for the participants. Providing material incentives for thousands or millions of people, as well as the related administrative effort of study management, may simply not be feasible.

In the not-so-distant future, many studies of human behavior will move towards accessing already existing personal data. Even today we can access mobility of large populations, by mining data from Twitter, Facebook, or Flickr. Or, with participants' authorizations, we can track their activity levels, using APIs of self-tracking services such as Fitbit or RunKeeper. Linking across multiple streams is still difficult today (the problem of data silos), but as users take more control over their personal data, scientific studies can become consumers rather than producers of the existing personal data.

This process will pose new challenges and amplify the existing ones, such as the replicability and reproducibility of the results or selection bias in the context of full end-user data control. Still, we expect that future studies will increasingly rely on the existing data, and it is important to understand how the incomplete view we get from such data influences our results. For this reason, we need research testbeds—such as the Copenhagen Networks Study—where we study 'deep data' in the sense of multi layered data streams, sampled with high temporal resolution. These deep data will allow us to unlock and understand the future streams of big data.

9 Acknowledgments

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References

1. Ginsberg J, Mohebbi MH, Patel RS, Brammer L, Smolinski MS, et al. (2008) Detecting influenza epidemics using search engine query data. *Nature* 457: 1012–1014.
2. Aral S, Walker D (2012) Identifying influential and susceptible members of social networks. *Science* 337: 337–341.
3. Onnela JP, Saramäki J, Hyvönen J, Szabó G, Lazer D, et al. (2007) Structure and tie strengths in mobile communication networks. *Proceedings of the National Academy of Sciences* 104: 7332–7336.
4. Cha M, Haddadi H, Benevenuto F, Gummadi PK (2010) Measuring user influence in Twitter: The million follower fallacy. *ICWSM 10*: 10–17.
5. Shalizi CR, Thomas AC (2011) Homophily and contagion are generically confounded in observational social network studies. *Sociological Methods & Research* 40: 211–239.
6. Barabási AL, Jeong H, Néda Z, Ravasz E, Schubert A, et al. (2002) Evolution of the social network of scientific collaborations. *Physica A: Statistical Mechanics and its Applications* 311: 590–614.
7. Kossinets G, Watts DJ (2006) Empirical analysis of an evolving social network. *Science* 311: 88–90.
8. Lazer D, Pentland A, Adamic L, Aral S, Barabási A, et al. (2009) Life in the network: the coming age of computational social science. *Science (New York, NY)* 323: 721.
9. Wesolowski A, Eagle N, Noor AM, Snow RW, Buckee CO (2013) The impact of biases in mobile phone ownership on estimates of human mobility. *Journal of The Royal Society Interface* 10: 20120986.
10. Madrigal A (2013) Dark social: We have the whole history of the web wrong. *The Atlantic* .

11. Cattuto C, Van den Broeck W, Barrat A, Colizza V, Pinton JF, et al. (2010) Dynamics of person-to-person interactions from distributed RFID sensor networks. *PloS one* 5: e11596.
12. Wu L, Waber B, Aral S, Brynjolfsson E, Pentland A (2008) Mining face-to-face interaction networks using sociometric badges: Predicting productivity in an IT configuration task. Available at SSRN 1130251 .
13. Polastre J, Szewczyk R, Culler D (2005) Telos: enabling ultra-low power wireless research. In: *Information Processing in Sensor Networks*, 2005. IPSN 2005. Fourth International Symposium on. IEEE, pp. 364–369.
14. Raento M, Oulasvirta A, Eagle N (2009) Smartphones an emerging tool for social scientists. *Sociological methods & research* 37: 426–454.
15. Chronis I, Madan A, Pentland AS (2009) SocialCircuits: the art of using mobile phones for modeling personal interactions. In: *Proceedings of the ICMI-MLMI'09 Workshop on Multimodal Sensor-Based Systems and Mobile Phones for Social Computing*. ACM, p. 1.
16. Pentland AS (2008) *Honest Signals: how they shape our world*. MIT Press.
17. Olguín D, Madan A, Cebrian M, Pentland A (2011) Mobile sensing technologies and computational methods for collective intelligence. *Next Generation Data Technologies for Collective Computational Intelligence* : 575–597.
18. Miller G (2012) The smartphone psychology manifesto. *Perspectives on Psychological Science* 7: 221–237.
19. Raento M, Oulasvirta A, Petit R, Toivonen H (2005) ContextPhone: A prototyping platform for context-aware mobile applications. *Pervasive Computing, IEEE* 4: 51–59.
20. Mulder I, Ter Hofte G, Kort J (2005) SocioXensor: Measuring user behaviour and user experience in context with mobile devices. In: *Proceedings of Measuring Behavior*. pp. 355–358.
21. Froehlich J, Chen MY, Consolvo S, Harrison B, Landay JA (2007) MyExperience: a system for in situ tracing and capturing of user feedback on mobile phones. In: *Proceedings of the 5th international conference on Mobile systems, applications and services*. ACM, pp. 57–70.
22. Cornelius C, Kapadia A, Kotz D, Peebles D, Shin M, et al. (2008) AnonySense: privacy-aware people-centric sensing. In: *Proceedings of the 6th international conference on Mobile systems, applications, and services*. ACM, pp. 211–224.
23. Miluzzo E, Lane N, Fodor K, Peterson R, Lu H, et al. (2008) Sensing meets mobile social networks: the design, implementation and evaluation of the CenceMe application. In: *Proceedings of the 6th ACM conference on Embedded network sensor systems*. ACM, pp. 337–350.
24. Kostakos V, O'Neill E (2008) Cityware: Urban computing to bridge online and real-world social networks. *Handbook of research on urban informatics: The practice and promise of the real-time city* : 195–204.
25. Miluzzo E, Cornelius C, Ramaswamy A, Choudhury T, Liu Z, et al. (2010) Darwin phones: the evolution of sensing and inference on mobile phones. In: *Proceedings of the 8th international conference on Mobile systems, applications, and services*. ACM, pp. 5–20.
26. Hu X, Leung VC, Chu TH, Chan HC (2013) Vita: A crowdsensing-oriented mobile cyber-physical system. *IEEE Transactions on Emerging Topics in Computing* 1: 148–165.

27. Larsen JE, Jensen K (2009) Mobile Context Toolbox. In: Smart Sensing and Context, Springer. pp. 193–206.
28. Eagle N, Pentland A (2006) Reality mining: sensing complex social systems. *Personal and Ubiquitous Computing* 10: 255–268.
29. (2013). Funf Open Sensing Framework. URL <http://funf.org/>. [Online; accessed 19-March-2014].
30. Aharony N, Pan W, Ip C, Khayal I, Pentland A (2011) Social fMRI: Investigating and shaping social mechanisms in the real world. *Pervasive and Mobile Computing* 7: 643–659.
31. Kiukkonen N, Blom J, Dousse O, Gatica-Perez D, Laurila J (2010) Towards rich mobile phone datasets: Lausanne data collection campaign. *Proc ICPS, Berlin* .
32. Laurila J, Gatica-Perez D, Aad I, Blom J, Bornet O, et al. (2012) The mobile data challenge: Big data for mobile computing research. In: *Mobile Data Challenge by Nokia Workshop*, in conjunction with *Int. Conf. on Pervasive Computing*, Newcastle, UK.
33. Olguín D, Waber B, Kim T, Mohan A, Ara K, et al. (2009) Sensible organizations: Technology and methodology for automatically measuring organizational behavior. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on* 39: 43–55.
34. Karikoski J, Nelimarkka M (2011) Measuring social relations with multiple datasets. *International Journal of Social Computing and Cyber-Physical Systems* 1: 98–113.
35. Cranshaw J, Toch E, Hong J, Kittur A, Sadeh N (2010) Bridging the gap between physical location and online social networks. In: *Proceedings of the 12th ACM International Conference on Ubiquitous Computing*. ACM, pp. 119–128.
36. González MC, Hidalgo CA, Barabási AL (2008) Understanding individual human mobility patterns. *Nature* 453: 779–782.
37. Song C, Qu Z, Blumm N, Barabási AL (2010) Limits of predictability in human mobility. *Science* 327: 1018–1021.
38. Sevtsuk A, Ratti C (2010) Does urban mobility have a daily routine? Learning from the aggregate data of mobile networks. *Journal of Urban Technology* 17: 41–60.
39. Bagrow JP, Lin YR (2012) Mesoscopic structure and social aspects of human mobility. *PLoS One* 7: e37676.
40. De Domenico M, Lima A, Musolesi M (2013) Interdependence and predictability of human mobility and social interactions. *Pervasive and Mobile Computing* 9: 798–807.
41. Eagle N, Pentland AS, Lazer D (2009) Inferring friendship network structure by using mobile phone data. *Proceedings of the National Academy of Sciences* 106: 15274–15278.
42. Eagle N, Pentland AS (2009) Eigenbehaviors: Identifying structure in routine. *Behavioral Ecology and Sociobiology* 63: 1057–1066.
43. Clauset A, Eagle N (2007) Persistence and periodicity in a dynamic proximity network. In: *DyDAn Workshop on Computational Methods for Dynamic Interaction Networks*.
44. Onnela JP, Saramäki J, Hyvönen J, Szabó G, De Menezes MA, et al. (2007) Analysis of a large-scale weighted network of one-to-one human communication. *New Journal of Physics* 9: 179.

45. Granovetter MS (1973) The strength of weak ties. *American Journal of Sociology* : 1360–1380.
46. Lambiotte R, Blondel VD, de Kerchove C, Huens E, Prieur C, et al. (2008) Geographical dispersal of mobile communication networks. *Physica A: Statistical Mechanics and its Applications* 387: 5317–5325.
47. Onnela JP, Arbesman S, González MC, Barabási AL, Christakis NA (2011) Geographic constraints on social network groups. *PLoS One* 6: e16939.
48. Hidalgo CA, Rodriguez-Sickert C (2008) The dynamics of a mobile phone network. *Physica A: Statistical Mechanics and its Applications* 387: 3017–3024.
49. Miritello G, Lara R, Cebrian M, Moro E (2013) Limited communication capacity unveils strategies for human interaction. *Scientific reports* 3.
50. Miritello G, Moro E, Lara R, Martínez-López R, Belchamber J, et al. (2013) Time as a limited resource: Communication strategy in mobile phone networks. *Social Networks* 35: 89–95.
51. Sun L, Axhausen KW, Lee DH, Huang X (2013) Understanding metropolitan patterns of daily encounters. *Proceedings of the National Academy of Sciences* 110: 13774–13779.
52. Kapoor A, Eagle N, Horvitz E (2010) People, quakes, and communications: Inferences from call dynamics about a seismic event and its influences on a population. In: *AAAI Spring Symposium: Artificial Intelligence for Development*.
53. Madan A, Cebrian M, Moturu S, Farrahi K, Pentland S (2012) Sensing the health state of a community. *IEEE Pervasive Computing* 11: 36–45.
54. Salathé M, Kazandjieva M, Lee JW, Levis P, Feldman MW, et al. (2010) A high-resolution human contact network for infectious disease transmission. *Proceedings of the National Academy of Sciences* 107: 22020–22025.
55. .
56. Wang P, González MC, Hidalgo CA, Barabási AL (2009) Understanding the spreading patterns of mobile phone viruses. *Science* 324: 1071–1076.
57. Isella L, Romano M, Barrat A, Cattuto C, Colizza V, et al. (2011) Close encounters in a pediatric ward: measuring face-to-face proximity and mixing patterns with wearable sensors. *PLoS One* 6: e17144.
58. Stehlé J, Voirin N, Barrat A, Cattuto C, Isella L, et al. (2011) High-resolution measurements of face-to-face contact patterns in a primary school. *PLoS One* 6: e23176.
59. Bagrow JP, Wang D, Barabási AL (2011) Collective response of human populations to large-scale emergencies. *PLoS One* 6: e17680.
60. Karsai M, Perra N, Vespignani A (2013) The emergence and role of strong ties in time-varying communication networks. *arXiv preprint arXiv:13035966* .
61. Christakis NA, Fowler JH (2007) The spread of obesity in a large social network over 32 years. *New England Journal of Medicine* 357: 370–379.
62. Christakis NA, Fowler JH (2008) The collective dynamics of smoking in a large social network. *New England Journal of Medicine* 358: 2249–2258.

63. Lyons R (2011) The spread of evidence-poor medicine via flawed social-network analysis. *Statistics, Politics, and Policy* 2.
64. Steglich C, Snijders TA, Pearson M (2010) Dynamic networks and behavior: Separating selection from influence. *Sociological Methodology* 40: 329–393.
65. Aral S, Muchnik L, Sundararajan A (2009) Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *Proceedings of the National Academy of Sciences* 106: 21544–21549.
66. Eagle N, Macy M, Claxton R (2010) Network diversity and economic development. *Science* 328: 1029–1031.
67. Blondel V, Krings G, Thomas I (2010) Regions and borders of mobile telephony in Belgium and in the Brussels metropolitan zone. *Brussels Studies* 42.
68. Mahato H, Kern D, Holleis P, Schmidt A (2008) Implicit personalization of public environments using Bluetooth. In: *CHI'08 extended abstracts on Human factors in computing systems*. ACM, pp. 3093–3098.
69. Klasnja P, Consolvo S, Choudhury T, Beckwith R, Hightower J (2009) Exploring privacy concerns about personal sensing. In: *Proceedings of the 7th International Conference on Pervasive Computing*. Berlin, Heidelberg: Springer-Verlag, Pervasive '09, pp. 176–183. doi: 10.1007/978-3-642-01516-8_13. URL http://dx.doi.org/10.1007/978-3-642-01516-8_13.
70. Altshuler Y, Aharoni N, Elovici Y, Pentland A, Cebrian M (2011) Stealing reality: when criminals become data scientists (or vice versa). *Security and Privacy in Social Networks* : 133–151.
71. Shokri R, Theodorakopoulos G, Le Boudec J, Hubaux J (2011) Quantifying location privacy. In: *Security and Privacy (SP), 2011 IEEE Symposium on*. IEEE, pp. 247–262.
72. Lane N, Xie J, Moscibroda T, Zhao F (2012) On the feasibility of user de-anonymization from shared mobile sensor data. In: *Proceedings of the Third International Workshop on Sensing Applications on Mobile Phones*. ACM, p. 3.
73. Srivatsa M, Hicks M (2012) Deanonymizing mobility traces: using social network as a side-channel. In: *Proceedings of the 2012 ACM conference on Computer and communications security*. ACM, pp. 628–637.
74. Mislove A, Viswanath B, Gummadi KP, Druschel P (2010) You are who you know: inferring user profiles in online social networks. In: *Proceedings of the third ACM International Conference on Web search and data mining*. ACM, pp. 251–260.
75. Zhou B, Pei J (2008) Preserving privacy in social networks against neighborhood attacks. In: *Data Engineering, 2008. ICDE 2008. IEEE 24th International Conference on*. IEEE, pp. 506–515.
76. Cheng J, Fu AWc, Liu J (2010) K-isomorphism: privacy preserving network publication against structural attacks. In: *Proceedings of the 2010 ACM SIGMOD International Conference on Management of data*. ACM, pp. 459–470.
77. Li T, Li N (2009) On the tradeoff between privacy and utility in data publishing. In: *Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM, pp. 517–526.

78. Narayanan A, Shmatikov V (2008) Robust de-anonymization of large sparse datasets. In: Security and Privacy, 2008. SP 2008. IEEE Symposium on. IEEE, pp. 111–125.
79. Sweeney L (2000) Simple demographics often identify people uniquely. *Health (San Francisco)* : 1–34.
80. Barbaro M, Zeller T, Hansell S (2006) A face is exposed for AOL searcher no. 4417749. *New York Times* 9: 8For.
81. de Montjoye YA, Hidalgo CA, Verleysen M, Blondel VD (2013) Unique in the crowd: The privacy bounds of human mobility. *Scientific reports* 3.
82. Sweeney L (2002) k-anonymity: A model for protecting privacy. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems* 10: 557–570.
83. Machanavajjhala A, Kifer D, Gehrke J, Venkatasubramanian M (2007) l-diversity: Privacy beyond k-anonymity. *ACM Transactions on Knowledge Discovery from Data (TKDD)* 1: 3.
84. Li N, Li T, Venkatasubramanian S (2007) t-closeness: Privacy beyond k-anonymity and l-diversity. In: *Data Engineering, 2007. ICDE 2007. IEEE 23rd International Conference on*. IEEE, pp. 106–115.
85. Dinur I, Nissim K (2003) Revealing information while preserving privacy. In: *Proceedings of the twenty-second ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems*. ACM, pp. 202–210.
86. Dwork C, Nissim K (2004) Privacy-preserving datamining on vertically partitioned databases. In: *Advances in Cryptology-CRYPTO 2004*. Springer, pp. 134–138.
87. Blum A, Dwork C, McSherry F, Nissim K (2005) Practical privacy: the SuLQ framework. In: *Proceedings of the twenty-fourth ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems*. ACM, pp. 128–138.
88. Dwork C, Kenthapadi K, McSherry F, Mironov I, Naor M (2006) Our data, ourselves: Privacy via distributed noise generation. *Advances in Cryptology-EUROCRYPT 2006* : 486–503.
89. Chawla S, Dwork C, McSherry F, Smith A, Wee H (2005) Toward privacy in public databases. *Theory of Cryptography* : 363–385.
90. Rivest RL, Adleman L, Dertouzos ML (1978) On data banks and privacy homomorphisms. *Foundations of secure computation* 4: 169–180.
91. Gentry C (2009) A fully homomorphic encryption scheme. Ph.D. thesis, Stanford University.
92. Tebaa M, El Hajji S (2012) Homomorphic encryption applied to the cloud computing security. In: *Proceedings of the World Congress on Engineering*. volume 1, pp. 4–6.
93. Naehrig M, Lauter K, Vaikuntanathan V (2011) Can homomorphic encryption be practical? In: *Proceedings of the 3rd ACM workshop on Cloud computing security workshop*. ACM, pp. 113–124.
94. Popa R, Balakrishnan H, Blumberg A (2009) VPriv: protecting privacy in location-based vehicular services. In: *Proceedings of the 18th conference on USENIX security symposium*. USENIX Association, pp. 335–350.

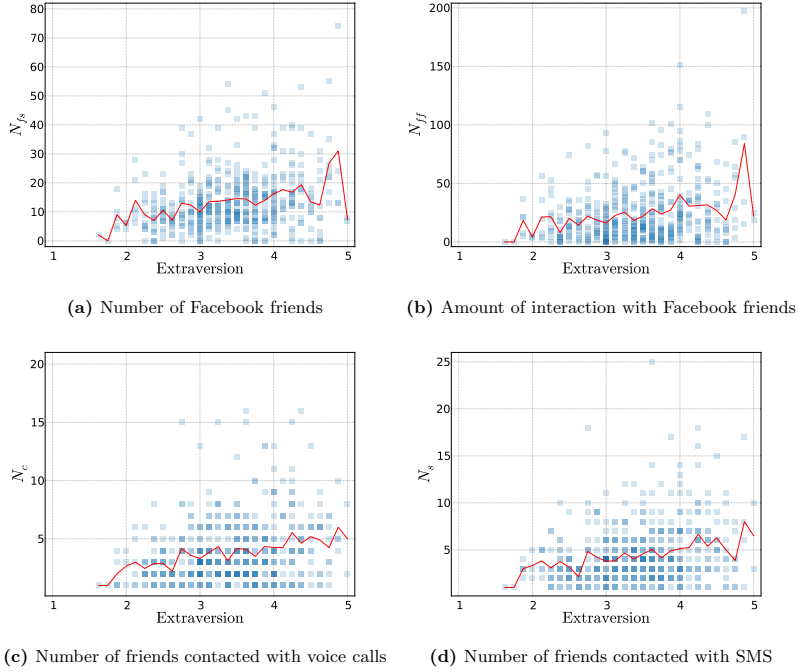
95. Molina A, Salajegheh M, Fu K (2009) HICCUPS: health information collaborative collection using privacy and security. In: Proceedings of the first ACM workshop on Security and privacy in medical and home-care systems. ACM, pp. 21–30.
96. Zdancewic SA (2002) Programming languages for information security. Ph.D. thesis, Cornell University.
97. Sfaxi L, Abdellatif T, Robbana R, Lakhnech Y (2010) Information flow control of component-based distributed systems. *Concurrency and Computation: Practice and Experience* .
98. Zeldovich N, Boyd-Wickizer S, Mazières D (2008) Securing distributed systems with information flow control. In: Proceedings of the 5th USENIX Symposium on Networked Systems Design and Implementation. USENIX Association, pp. 293–308.
99. Mundada Y, Ramachandran A, Feamster N (2011) Silverline: data and network isolation for cloud services. In: Proceedings of the 3rd USENIX conference on Hot topics in cloud computing. USENIX Association, pp. 13–13.
100. Pappas V, Kemerlis V, Zavou A, Polychronakis M, Keromytis AD (2012) CloudFence: Enabling users to audit the use of their cloud-resident data .
101. Ganjali A, Lie D (2012) Auditing cloud administrators using information flow tracking. In: Proceedings of the 2012 ACM Conference on Computer and Communications Security (CCS). pp. 79–84.
102. Boneh D, Lipton R (1996) A revocable backup system. In: USENIX Security Symposium. pp. 91–96.
103. Perlman R (2005) The ephemerizer: Making data disappear. Technical report, Mountain View, CA, USA.
104. Perlman R (2005) File system design with assured delete. In: Security in Storage Workshop, 2005. SISW'05. Third IEEE International. IEEE, pp. 6–pp.
105. Geambasu R, Kohno T, Levy A, Levy HM (2009) Vanish: Increasing data privacy with self-destructing data. In: Proc. of the 18th USENIX Security Symposium. p. 56.
106. Agrawal R, Haas PJ, Kiernan J (2003) Watermarking relational data: framework, algorithms and analysis. *The VLDB journal* 12: 157–169.
107. Cox IJ, Miller ML, Bloom JA (2000) Watermarking applications and their properties. In: Information Technology: Coding and Computing, 2000. Proceedings. International Conference on. IEEE, pp. 6–10.
108. Cox IJ, Linnartz JP (1998) Some general methods for tampering with watermarks. *Selected Areas in Communications, IEEE Journal on* 16: 587–593.
109. Cattuto C, Van den Broeck W, Barrat A, Colizza V, Pinton JF, et al. (2010) Dynamics of person-to-person interactions from distributed RFID sensor networks. *PLoS One* 5: e11596.
110. Larsen JE, Sapiezynski P, Stopczynski A, Mørup M, Theodorsen R (2013) Crowds, Bluetooth, and Rock'N'Roll: Understanding music festival participant behavior. In: Proceedings of the 1st ACM International Workshop on Personal Data Meets Distributed Multimedia. New York, NY, USA: ACM, PDM '13, pp. 11–18. doi:10.1145/2509352.2509399. URL <http://doi.acm.org/10.1145/2509352.2509399>.

111. Ranjan G, Zang H, Zhang ZL, Bolot J (2012) Are call detail records biased for sampling human mobility? *SIGMOBILE Mob Comput Commun Rev* 16: 33–44.
112. Isaacman S, Becker R, Cáceres R, Kobourov S, Martonosi M, et al. (2011) Identifying important places in peoples lives from cellular network data. In: *Pervasive Computing*, Springer. pp. 133–151.
113. Mucha P, Richardson T, Macon K, Porter M, Onnela JP (2010) Community structure in time-dependent, multiscale, and multiplex networks. *Science* 328: 876–878.
114. Szell M, Lambiotte R, Thurner S (2010) Multirelational organization of large-scale social networks. *Proceedings of the National Academy of Sciences USA* 107: 13636–13641.
115. Madden M, Lenhart A, Cortesi S, Gasser U, Duggan M, et al. (2013). Teens, Social Media, and Privacy. URL http://www.pewinternet.org/~media/Files/Reports/2013/PIP_TeensSocialMediaandPrivacy.pdf. [Online; accessed 19-March-2014].
116. Kossinets G (2006) Effects of missing data in social networks. *Social Networks* 28: 247–268.
117. Laumann E, Marsden P, Prensky D (1983) *The boundary specification problem in network analysis*, Sage Publications. pp. 18–34.
118. Saramäki J, Leicht E, López E, Roberts SG, Reed-Tsochas F, et al. (2014) Persistence of social signatures in human communication. *Proceedings of the National Academy of Sciences* 111: 942–947.
119. Holme P, Saramäki J (2012) Temporal networks. *Physics reports* 519: 97–125.
120. Shalizi C, Thomas A (2011) Homophily and contagion are generically confounded in observational social network studies. *Sociological Methods & Research* 40: 211–239.
121. Fowler J, Christakis N (2008) Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham heart study. *British Medical Journal* 337: a2338.
122. Christakis N, Fowler J (2009) *Connected: the surprising power of our social networks and how they shape our lives*. Little, Brown and Company.
123. Li I, Dey A, Forlizzi J (2010) A stage-based model of personal informatics systems. In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, pp. 557–566.
124. Larsen JE, Cuttane A, Jørgensen SL (2013) QS Spiral: Visualizing periodic quantified self data. In: *CHI 2013 Workshop on Personal Informatics in the Wild: Hacking Habits for Health & Happiness*.
125. Cuttane A, Lehmann S, Larsen JE (2013) A mobile personal informatics system with interactive visualizations of mobility and social interactions. In: *Proceedings of the 1st ACM international workshop on Personal data meets distributed multimedia*. ACM, pp. 27–30.
126. Rocha L, Liljeros F, Holme P (2011) Simulated epidemics in an empirical spatiotemporal network of 50,185 sexual contacts. *PLoS Computational Biology* 7: e1001109.
127. Lee S, Rocha LE, Liljeros F, Holme P (2012) Exploiting temporal network structures of human interaction to effectively immunize populations. *PloS One* 7: e36439.
128. Fortunato S (2010) Community detection in graphs. *Physics Reports* 486: 75 - 174.

129. Gulbahce N, Lehmann S (2008) The art of community detection. *BioEssays* 30: 934–938.
130. Ahn YY, Bagrow JP, Lehmann S (2010) Link communities reveal multiscale complexity in networks. *Nature* 466: 761–764.
131. Fiedler M (1975) A property of eigenvectors of nonnegative symmetric matrices and its application to graph theory. *Czechoslovak Mathematical Journal* 25: 619.
132. Bagrow JP, Lehmann S, Ahn YY (2011). Robustness and modular structure in networks. *arxiv/1102.5085*.
133. (2013). Facebook reports first quarter 2013 results. URL <http://investor.fb.com/releasedetail.cfm?ReleaseID=761090>. [Online; accessed 19-March-2014].
134. John OP, Srivastava S (1999) The big five trait taxonomy: History, measurement, and theoretical perspectives. *Handbook of personality: Theory and research* 2: 102–138.
135. Rosenberg M (1989) *Society and the adolescent self-image* (rev). Wesleyan University Press.
136. Back MD, Küfner AC, Dufner M, Gerlach TM, Rauthmann JF, et al. (2013) Narcissistic admiration and rivalry: Disentangling the bright and dark sides of narcissism. *Journal of Personality and Social Psychology* 105: 1013.
137. Diener E, Emmons RA, Larsen RJ, Griffin S (1985) The satisfaction with life scale. *Journal of personality assessment* 49: 71–75.
138. Rotter JB (1966) Generalized expectancies for internal versus external control of reinforcement. *Psychological monographs: General and applied* 80: 1.
139. Russell DW (1996) UCLA loneliness scale (version 3): Reliability, validity, and factor structure. *Journal of personality assessment* 66: 20–40.
140. Sherer M, Maddux JE, Mercandante B, Prentice-Dunn S, Jacobs B, et al. (1982) The self-efficacy scale: Construction and validation. *Psychological reports* 51: 663–671.
141. Cohen S, Kamarck T, Mermelstein R (1983) A global measure of perceived stress. *Journal of health and social behavior* : 385–396.
142. Bech P, Rasmussen NA, Olsen LR, Noerholm V, Abildgaard W (2001) The sensitivity and specificity of the major depression inventory, using the present state examination as the index of diagnostic validity. *Journal of affective disorders* 66: 159–164.
143. Lund R, Nielsen LS, Henriksen PW, Schmidt L, Avlund K, et al. (2014) Content validity and reliability of the Copenhagen Social Relations Questionnaire. *Journal of aging and health* 26: 128–150.
144. Watson D, Clark LA, Tellegen A (1988) Development and validation of brief measures of positive and negative affect: the PANAS scales. *Journal of personality and social psychology* 54: 1063.
145. Ellen RF, Firth R (1984) *Ethnographic research: A guide to general conduct*. Academic Press London.
146. de Montjoye YA, Wang SS, Pentland A, Anh DTT, Datta A, et al. (2012) On the trusted use of large-scale personal data. *IEEE Data Eng Bull* 35: 5–8.

147. Shampanier K, Mazar N, Ariely D (2007) Zero as a special price: The true value of free products. *Marketing Science* 26: 742–757.
148. Stopczynski A, Pietri R, Pentland A, Lazer D, Lehmann S (2014) Privacy in Sensor-Driven Human Data Collection: A Guide for Practitioners. *arXiv preprint arXiv:14035299*.
149. (2013). SensibleDTU informed consent form (da). URL https://github.com/MIT-Model-Open-Data-and-Identity-System/SensibleData-Service/blob/production_sensibledtu1k/sensible_data_service/documents/service_informed_consent_da.txt.
150. (2013). SensibleDTU informed consent form (en). URL https://github.com/MIT-Model-Open-Data-and-Identity-System/SensibleData-Service/blob/production_sensibledtu1k/sensible_data_service/documents/service_informed_consent_en.txt.
151. Sekara V, Lehmann S (2014) Application of network properties and signal strength to identify face-to-face links in an electronic dataset. *arXiv preprint arXiv:14015836*.
152. Stopczynski A, Larsen JE, Lehmann S, Dynowski L, Fuentes M (2013) Participatory Bluetooth sensing: A method for acquiring spatio-temporal data about participant mobility and interactions at large scale events. In: *Pervasive Computing and Communications Workshops (PERCOM Workshops)*, 2013 IEEE International Conference on. IEEE, pp. 242–247.
153. Krings G, Karsai M, Bernhardsson S, Blondel VD, Saramäki J (2012) Effects of time window size and placement on the structure of an aggregated communication network. *EPJ Data Science* 1: 1–16.
154. Ribeiro B, Nicola P, Baronchelli A (2013) Quantifying the effect of temporal resolution on time-varying networks. *Scientific reports* 3.
155. Whitehead M, Phillips T, Page M, Molina M, Wood C (2012). European mobile industry observatory 2011. URL <http://www.gsma.com/publicpolicy/wp-content/uploads/2012/04/emofullwebfinal.pdf>. [Online; accessed 19-March-2014].
156. LaMarca A, Chawathe Y, Consolvo S, Hightower J, Smith I, et al. (2005) Place Lab: Device positioning using radio beacons in the wild. In: *Pervasive Computing*, Springer. pp. 116–133.
157. Kjærgaard MB, Nurmi P (2012) Challenges for Social Sensing Using WiFi Signals. In: *Proceedings of the 1st ACM workshop on Mobile systems for computational social science*. New York, NY, USA: ACM, MCSS '12, pp. 17–21. doi:10.1145/2307863.2307869. URL <http://doi.acm.org/10.1145/2307863.2307869>.
158. Carlotto A, Parodi M, Bonamico C, Lavagetto F, Valla M (2008) Proximity classification for mobile devices using Wi-Fi environment similarity. In: *Proceedings of the first ACM international workshop on Mobile entity localization and tracking in GPS-less environments*. ACM, pp. 43–48.
159. Carreras I, Matic A, Saar P, Osmani V (2012) Comm2Sense: Detecting proximity through smart-phones. In: *Pervasive Computing and Communications Workshops (PERCOM Workshops)*, 2012 IEEE International Conference on. IEEE, pp. 253–258.
160. Lin M, Hsu WJ (2013) Mining GPS data for mobility patterns: A survey. *Pervasive and Mobile Computing*.
161. (2013). statsmodels.nonparametric.kde.kdeunivariate. URL <http://statsmodels.sourceforge.net/devel/generated/statsmodels.nonparametric.kde.KDEUnivariate.html>. [Online; accessed 19-March-2014].

162. Hariharan R, Toyama K (2004) Project Lachesis: parsing and modeling location histories. In: *Geographic Information Science*, Springer. pp. 106–124.
163. Zheng Y, Zhang L, Xie X, Ma WY (2009) Mining interesting locations and travel sequences from GPS trajectories. In: *Proceedings of the 18th international conference on World wide web*. ACM, pp. 791–800.
164. Montoliu R, Gatica-Perez D (2010) Discovering human places of interest from multimodal mobile phone data. In: *Proceedings of the 9th International Conference on Mobile and Ubiquitous Multimedia*. ACM, p. 12.
165. Zheng VW, Zheng Y, Xie X, Yang Q (2010) Collaborative location and activity recommendations with GPS history data. In: *Proceedings of the 19th international conference on World Wide Web*. ACM, pp. 1029–1038.
166. Palla G, Barabási AL, Vicsek T (2007) Quantifying social group evolution. *Nature* 446: 664–667.
167. (2013). “Facebook Reports Third Quarter Results”. URL <http://investor.fb.com/releasedetail.cfm?ReleaseID=802760>. [Online; accessed 19-March-2014].
168. McPherson M, Smith-Lovin L, Cook JM (2001) Birds of a feather: Homophily in social networks. *Annual review of sociology* : 415–444.
169. Blüml V, Kapusta ND, Doering S, Brähler E, Wagner B, et al. (2013) Personality factors and suicide risk in a representative sample of the german general population. *PloS One* 8: e76646.
170. Schmitt DP, Allik J, McCrae RR, Benet-Martínez V (2007) The geographic distribution of big five personality traits patterns and profiles of human self-description across 56 nations. *Journal of Cross-Cultural Psychology* 38: 173–212.
171. Quercia D, Lambiotte R, Stillwell D, Kosinski M, Crowcroft J (2012) The personality of popular facebook users. In: *Proceedings of the ACM 2012 conference on computer supported cooperative work*. ACM, pp. 955–964.
172. Swickert RJ, Rosentreter CJ, Hittner JB, Mushrush JE (2002) Extraversion, social support processes, and stress. *Personality and Individual Differences* 32: 877–891.
173. Staiano J, Lepri B, Aharony N, Pianesi F, Sebe N, et al. (2012) Friends don’t lie: inferring personality traits from social network structure. In: *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*. ACM, pp. 321–330.
174. Chittaranjan G, Blom J, Gatica-Perez D (2011) Who’s who with big-five: Analyzing and classifying personality traits with smartphones. In: *Wearable Computers (ISWC), 2011 15th Annual International Symposium on*. IEEE, pp. 29–36.
175. Kalish Y, Robins G (2006) Psychological predispositions and network structure: The relationship between individual predispositions, structural holes and network closure. *Social Networks* 28: 56–84.
176. de Montjoye YA, Quoidbach J, Robic F, Pentland AS (2013) Predicting personality using novel mobile phone-based metrics. In: *Social Computing, Behavioral-Cultural Modeling and Prediction*, Springer. pp. 48–55.



| Personality trait | N_{fs} | N_{ff} | N_c | N_s |
|-------------------|----------|----------|---------|---------|
| Openness | — | — | — | — |
| Conscientiousness | — | 0.10* | — | — |
| Extraversion | 0.28*** | 0.25*** | 0.24*** | 0.25*** |
| Agreeableness | — | — | 0.09* | — |
| Neuroticism | — | — | — | — |

(e) Pearson correlation between Big Five Inventory personality traits and number of Facebook friends N_{fs} , volume of interactions with these friends N_{ff} , number of friends contacted via voice calls N_c and via SMS N_s . *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$

Figure 15. Correlation between personality traits and communication. Data from the 2013 deployment for $N=488$ participants, showing communication only with other study participants. Extraversion, the only significant feature across all networks is plotted. The red line indicates mean value within personality trait. Random spikes are due to small number of participants with extreme values.

APPENDIX C

The Strength of the Strongest Ties in Collaborative Problem Solving

Yves-Alexandre de Montjoye, **Arkadiusz Stopczynski**, Erez Shmueli, Alex ‘Sandy’ Pentland, and Sune Lehmann. The Strength of the Strongest Ties in Collaborative Problem Solving. *Under Review in Scientific Reports* (2014).

The Strength of the Strongest Ties in Collaborative Problem Solving

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Complex problem solving in science, engineering, and business has become a highly collaborative endeavor. Teams of scientists or engineers collaborate on projects using their social networks to gather new ideas and feedback. Here we bridge the literature on team performance and information networks by studying teams’ problem solving abilities as a function of both their within-team networks and their members’ extended networks. We show that, while an assigned team’s performance is strongly correlated with its networks of expressive and instrumental ties, only the strongest ties in both networks have an effect on performance. Both networks of strong ties explain more of the variance than other factors, such as measured or self-evaluated technical competencies, or the personalities of the team members. In fact, the inclusion of the network of strong ties renders these factors non-significant in the statistical analysis. Our results have consequences for the organization of teams of scientists, engineers, and other knowledge workers tackling today’s most complex problems.

Complex problems in science, engineering, or business are being solved by teams of people working closely with one another, each with the help of their network. In science, modern experiments require the collaboration and specialization of many individuals ¹. For example, a modern Nature paper can have more than 100 co-authors ² and the number of co-authors of PNAS papers has more than doubled over the last 20 years, reaching an average of 8.4 co-authors per paper ³. In businesses, teams of knowledge workers have become the basic unit carrying out work ⁴. Our ability to solve complex problems increasingly depends on teams of scientists, engineers, or

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knowledge workers and their extended information networks^{5,6}.

Qualitative and quantitative study of high-performing teams—an interdependent collection of individuals working towards a common goal where members share individual and mutual responsibility for the outcome⁷—has been an ongoing effort in the social, management, and science of science^{8–13}. Previous studies focused on how the personalities, technical or cognitive abilities, or the existence of previous collaborations of team members explain team performance. Recent quantitative studies investigated the determinants of high-performing teams by studying their structure or pattern of communications^{14–19}.

Accessing to the right piece of information is central to solving complex problems. This information, however, often only exists in the form of advice, expertise, implicit knowledge, or experience and flows through social ties. Consequently, the structure of social interactions has been shown to enhance or hinder access to such resources. Building on advances in social network analysis, empirical research showed the impact of an individual’s information or collaboration network on her performance^{20–26}. Amongst others, the impact of an individual position in the information network has been investigated through measures of node degree, centrality, structural holes, closure, and social diversity^{27–32}.

Both within-team and extended information networks are useful. Within-team networks allow for engagement, collaboration, and the higher level of information sharing needed for teams to perform¹⁵. Frequent interactions between team members have been shown to help them become familiar with one another and to positively impact their teamwork³³. Extended networks of informal ties of team members have been shown to be the vector for key exchanges of information¹⁵. Information often flows through these ties despite the existence of formal coordination and communication mechanisms. These informal extended ties have been shown to be particularly important in competitive environments³⁴. This work, at the intersection of information networks and team performance, studies the problem solving abilities of teams as a function of the within-team network structure and extended information network in a real working environment. We show that,

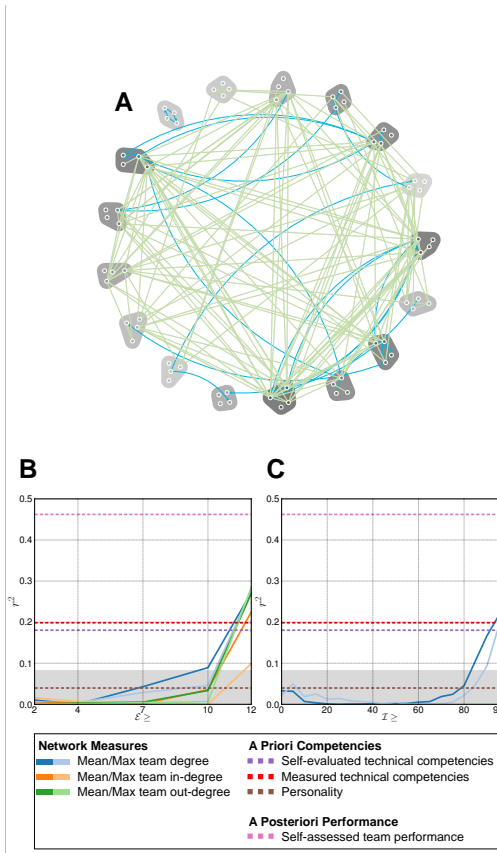


Figure 1: **A)** Network of strongest expressive ($\mathcal{E} \geq 12$ - blue), instrumental ($\mathcal{I} \geq 95$ - green), and team participants assigned to the first project. Color saturation is the performance of the teams, where darker is higher. **B)** Correlation between expressive tie strength and team performance. **C)** Correlation between instrumental tie strength and team performance. For both expressive and instrumental ties, the position in the network of strong ties is more important than other a priori characteristics of the team, such as self-evaluated and measured proficiency or personality. The gray areas indicate values with $p > 0.05$.

for both within team and extended ties networks, only the strongest ties matter.

Results

We examine the performance of 45 assigned teams of four students during one semester. Eighty participants worked in teams on three separate projects for one course. Teams changed for every project so that no one worked with the same person twice. Following the behavioral tradition of organizational learning, we measure performance by focusing on predefined objective outcomes³⁵: the grades given by the lecturer to the team reports. Participants specifically mark their individual contribution, which motivates them to actively participate.

There has been considerable ambiguity about what constitutes a tie when studying social and information networks, as well as the structure of organizations^{36,37}. In his definition of Phillos relationships, Karckhardt²³ focuses on interaction, affection, and time as the basic characteristics of ties. This prompted Lincoln to propose to define ties as either instrumental or expressive^{17,38}. We adopt this definition here.

Expressive ties reflect friendships and include an affective factor. They have been theorized to create incentives to treat others positively and fairly. We measured expressive ties using a questionnaire at the beginning of the experiment. Participants were asked to report their friendship levels (\mathcal{E}) on a 0, 2, 4, 7, 10, 12 scale, following the standard local grading system, with zero being “I do not know this person,” four “an acquaintance,” and twelve “one of my best friends” [see Methods]. We take friendship as a school-related measure of closeness. Fig. 2A shows the directed network of expressive ties, as well as the teams we assigned participants to for the first project.

Instrumental ties usually arise in professional settings, between colleagues or collaborators interacting and spending time together. They have been shown in the performance literature to create opportunities for the exchange of information²³, to develop an esprit de corps¹⁵, and to

allow for colleagues or collaborators to gain interpersonal familiarity³³. We consider time spent in physical proximity as a proxy for instrumental ties^{39,40}. The logs of the university wifi system indicates the building in which participants' devices were. Using this information, we construct a weighted undirected network of time spent together over the course of the semester (\mathcal{I}) on a 0 to 100 scale [see Methods]. Fig. 2B shows the undirected network of instrumental ties.

Finally, the impact of tie strength on information propagation and knowledge transfer has been discussed in the social network, sociology, and science of science literature. It has however been considered in the form of either strong or weak ties, with research showing benefits for both²¹. In his seminal article on job searches, Granovetter showed that opportunities such as information about jobs usually flow through weak ties²². Subsequent work showed these distant and infrequent weak ties to be useful in the diffusion of information, advice, and ideas^{41–43}. However, because they are more accessible or willing to help, strong ties have been shown to be essential to the transfer of complex information and tacit knowledge^{23–25,31}. In organizational settings, strong ties have been shown to reduce conflicts⁴⁴ and to be crucial in dealing with stressful or unusual situations²³. While quantifying what constitutes a strong and weak tie might be difficult, the effect of the expected benefits as a function of tie strength can be quantified.

We show that, given a simple linear model, the impact of tie strength on performance is highly nonlinear; only the strongest ties matter. We compute various network measures considered in the social network, collaboration network, and team performance literature such as the mean team degree, maximum team in-degree, etc¹⁷. All these measures display a nonlinear performance gain with tie strength; only the strongest expressive and instrumental ties (resp. $\mathcal{E} \geq 12$ and $\mathcal{I} \geq 95$) explain part of the team performance variance [Fig. 1]. All the network measures for the strongest ties are furthermore highly consistent internally ($\alpha = .940$)⁴⁵. The correlation between team performance and mean team degree is $r^2 = .272$ ($p < .05$) for strongest expressive ties and $r^2 = .214$ ($p < .05$) for the strongest instrumental ties. In comparison, the correlation between team performance with the weakest expressive and instrumental ties is respectively $r^2 = .010$ and $r^2 = .034$ (both $p > .05$). This implies that (1) for both within-team and extended networks,

only the strongest expressive and instrumental ties have an actual impact on the performance of the teams, and (2) the more expressive ties a team has, the better it performs.

Network measures of the strongest ties explain team performance better than other a priori measures, making them not significant most of the time. At the beginning of the experiment, participants took a 6-questions technical competencies test on the topic at hand, filled out a personality questionnaire, and were asked to self-evaluate how knowledgeable they were about the topic. The six technical questions were averaged as measured technical competency. The strongest ties in both the expressive and instrumental ties networks explain more of the variance than any of the team competencies considered: the mean or maximum of either the self-evaluated competencies, measured competencies, or personality [Fig. 1 and Methods]. The maximum self-evaluated and measured technical competencies, or personality, were systematically less explanatory than their mean values. None of the personality measures alone or combined as factors are significant. When taken as the only independent variable in a linear model, both mean self-evaluated ($p = .004$) and mean measured technical proficiency ($p = .002$) are significant. However, adding mean team degree of the strongest ties to both linear models makes both of them not significant ($p > .05$). Mean team degree for expressive ties has p -values of .009 when combined with mean self-evaluated proficiency and .014 when combined with mean measured proficiency (respectively .043 and .094 for instrumental ties).

Network measures of both expressive and instrumental ties explain performance better than self-evaluated and measured technical competencies, or personality. As a measure of comparison, participants were also asked to fill out a short questionnaire when handing in their projects. In this questionnaire, they were asked how they felt their team performed for this particular project. We expected this a posteriori measure to be the best indicator of team performance as self-assessment has been shown to be a reliable indicator of team performance⁴⁶. It indeed was. However, while a posteriori self-assessed team performance explains nearly half of the variance ($r^2 = .462$, $p < .001$), it is only two times what is explained by our a priori strong ties measures.

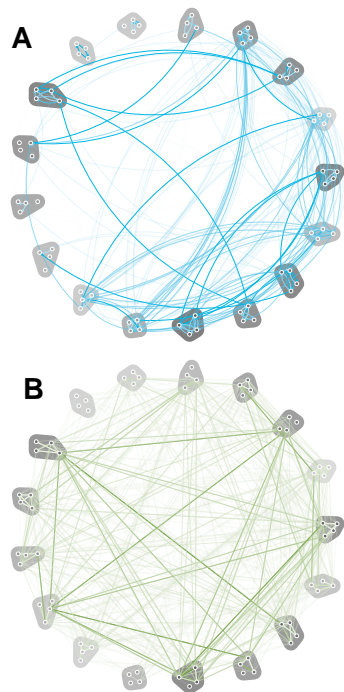


Figure 2: Networks of instrumental and expressive ties, as well as assigned teams for the first project. Color saturation is the performance of the team, where darker is higher. **A)** Directed network of expressive ties of strength four and above. **B)** Undirected network of the 20% strongest instrumental ties.

Discussion

Temporal precedence has been often neglected in team performance, collaboration networks, and social network research ^{19,47}. Our experimental design allows us to answer the question of temporal precedence between expressive network structure and team performance. Does a dense network

structure help a team to perform well or does a performing team create dense networks? In this study, we measured the network of expressive ties before the experiment started. We then assigned participants to teams, and we see a positive correlation between the strongest expressive ties and team performance.

Our results hold in both expressive and instrumental networks. Our expressive network is measured through traditional questionnaires, while our instrumental network is measured through sociometric means. We do not however expect the strength of a tie in the two networks to be independent as we are, for example, likely to spend more time with our friends. Fig. 3 shows that, while we indeed spend more time with our strongest expressive ties, the distribution of instrumental strength is still broad. This means that ties in both networks really help explain performance.

Tie strength, a variable often ignored, is in fact crucial for understanding teams' problem solving abilities. In our experiment, the project-based work completed by the participants can be characterized as non-routine and complex. Teams were presented with complex problems which focused on creative thinking and applying gained knowledge in a novel context.

To conclude, these results imply that weak ties between scientists, engineers, or other knowledge workers are unlikely to enhance access to information or to help performance. Very strong ties inside teams and between units or research teams are needed. The problem solving abilities of teams of scientists or knowledge workers tackling today's most complex problems could be greatly improved upon by creating very strong instrumental and expressive ties.

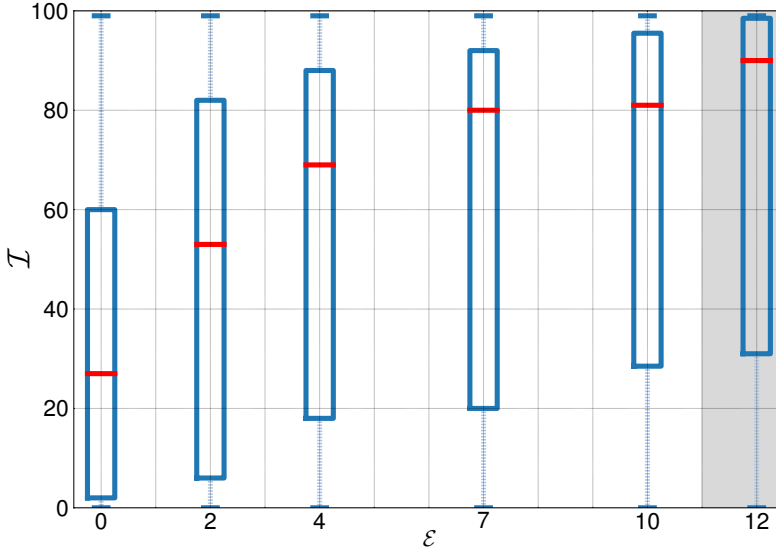


Figure 3: As expected, the strength of ties in expressive and instrumental networks is not independent. The distribution of \mathcal{I} for various \mathcal{E} is however broad. Instrumental tie strength for the strongest expressive ties ($\mathcal{E} = 12$ - in grey) has a large support. This means that the strongest ties in both networks really help explain performance.

Methods

Setup This experiment took place during a full semester course (13 weeks) at a large western university⁴⁸. The course was an advanced course, involving work with high-level programming, data modelling, and simple machine learning. At the beginning of the course, 80 out of the 95 students agreed to participate in the experiment and filled in an initial questionnaire. During the semester, participants successively worked on 3 projects in teams assigned by us. $N = 45$ teams contain-

ing only participants are analyzed in this paper. Participants also answered right after handing-in their project report how they felt their team performed on a 1 to 5 scale: “How do you think your team did.” Participants were informed that this self-assessed performance would not be seen by the lecturer, nor used in the grading process. The team projects were evaluated by the lecturer taking the difficulty of the assignment into account. The assignments focused on handling and visualizing social data, machine learning, and network analysis with students solving coding exercises, answering theoretical questions, and analyzing their results. At the university, students are encouraged to and commonly work and solve tasks in teams.

Initial Questionnaire At the beginning of the experiment, we asked participants about their self-reported proficiency on a 1-5 scale (“Would you consider yourself a beginner (1) or an expert (5) for this course?”). We also presented them with 6 technical questions assessing their skills related to the course and their personality (BFI-10) ⁴⁹.

Expressive Ties At the beginning of the experiment, we asked participants to rate how well they knew all the other participants. We used the standard grading scale (0-12), which all participants are familiar with: “0 - I do not know this person,” “2 - I recognize this person, but we never talked,” “4 - Acquaintance (we talk or hang out sometimes),” “7 - Friend,” “10 - Close friend,” “12 - One of my best friends”. The list of participants to rate was presented as a webpage that included the participants’ full names and university profile pictures.

The graphs of expressive ties were created by removing all links weaker than a given value. For example, $\mathcal{E} \geq 7$ would be the network with only ties of strength at least 7. We calculated the in- and out-degrees of all nodes in the directed network, as well as their degree in the undirected network. The undirected network was created by considering only reciprocated ties after having removed the links weaker than a given value. Results are similar with all three measures [Fig. 1]

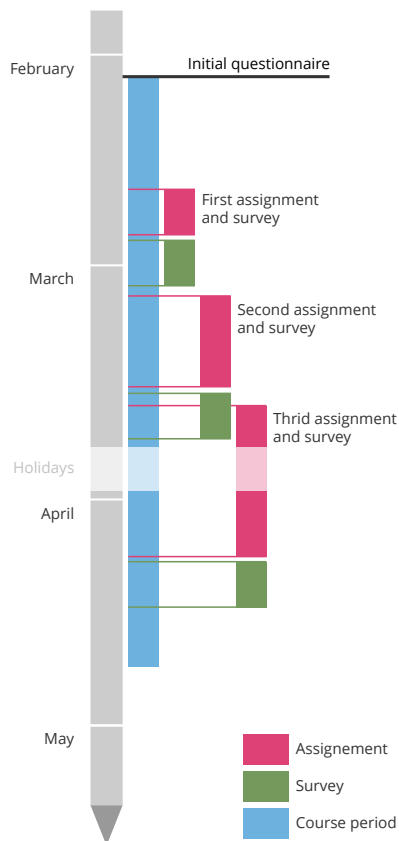


Figure 4: Timeline of the study. Students agree to participate in the study and fill in the initial questionnaire. They are then assigned to team, complete their assignment, and are asked how well they think their team did.

Instrumental Ties Participants have to login on their devices (smartphones, computers, etc) to use the university wifi system. This allows us to know which building a device was connected to with a resolution of 10 minutes. We infer instrumental ties from the observed co-occurrences using 10 minute time bins. The tie strength $S_{i,j}$ between participants i and j is given by ⁵⁰:

$$S_{i,j} = \sum_{t,b} \frac{c_{i,j,t,b}}{N_{t,b}} \quad (1)$$

where $c_{i,j,t,b}$ is 1 if participants were present in the same building b at the same time t and 0 if otherwise. $N_{t,b}$ is number of participants in building b at time t . We created the graphs of the wifi-based co-occurrences by percentiles. For example, $\mathcal{E} \geq 70$ would be the network with the 30% strongest ties.

Teams We assigned the participants into teams of four, as required by the course lecturer. We assigned students to new teams for each of the three projects so that no student was with the same person in team more than once. To find a balance among within and between team ties, we optimized the entropy of the motifs and the number of edges within teams while adding a penalty for missing motifs using a greedy algorithm [see SM].

Model The effects of ties of all strength, self-evaluated, and measured technical competencies and self-assessed team performance on the performance of teams were evaluated by computing Pearson’s product-moment coefficient between the team grade and the mean or the maximum of the measure of interest on a per team basis. The effect of personality was evaluated using both an average of the five personality traits of the team members as well as jointly modeled using a linear model with team grade as dependent variable. Finally, the effect of adding network measures to the self-evaluated and measured technical competencies and personalities of teams members were evaluated using a linear model.

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Contributions Y.-A. de M. designed the experiment, analyzed the data, and wrote the paper; A.S. and E.S. designed the experiment and analyzed the data; A.P. and S.L. designed the experiment and wrote the paper.

1. de Solla Price, D. J., de Solla Price, D. J., de Solla Price, D. J. & de Solla Price, D. J. *Little science, big science... and beyond* (Columbia University Press New York, 1986).
2. Greene, M. The demise of the lone author. *Nature* **450**, 1165–1165 (2007).
3. Börner, K., Maru, J. T. & Goldstone, R. L. The simultaneous evolution of author and paper networks. *PNAS* **101**, 5266–5273 (2004).
4. Beyerlein, M. M., Johnson, D. A. & Beyerlein, S. T. *Advances in interdisciplinary studies of work teams: Knowledge work in teams, Vol. 2.* (Elsevier Science/JAI Press, 1995).
5. Wuchty, S., Jones, B. F. & Uzzi, B. The increasing dominance of teams in production of knowledge. *Science* **316**, 1036–1039 (2007).
6. Lander, E. S. *et al.* Initial sequencing and analysis of the human genome. *Nature* **409**, 860–921 (2001).
7. Hackman, J. R. & Oldham, G. R. *Work redesign* (1980).
8. Hong, L. & Page, S. E. Groups of diverse problem solvers can outperform groups of high-ability problem solvers. *PNAS* **101**, 16385–16389 (2004).
9. Stokols, D., Hall, K. L., Taylor, B. K. & Moser, R. P. The science of team science: overview of the field and introduction to the supplement. *American Journal of Preventive Medicine* **35**, S77–S89 (2008).

10. Hackman, J. R. The design of work teams. *Ariel* **129**, 32–197 (1987).
11. Hackman, J. R. & Hackman, J. R. Groups that work (and those that don't): Creating conditions for effective teamwork (1990).
12. Cummings, J. N. & Cross, R. Structural properties of work groups and their consequences for performance. *Social Networks* **25**, 197–210 (2003).
13. Sanna, L. J. & Parks, C. D. Group research trends in social and organizational psychology: Whatever happened to intragroup research? *Psychological Science* **8**, 261–267 (1997).
14. Saavedra, S., Hagerty, K. & Uzzi, B. Synchronicity, instant messaging, and performance among financial traders. *PNAS* **108**, 5296–5301 (2011).
15. Pentland, A. The new science of building great teams. *Harvard Business Review* **90**, 60–69 (2012).
16. Wu, L., Waber, B., Aral, S., Brynjolfsson, E. & Pentland, A. Mining face-to-face interaction networks using sociometric badges: Predicting productivity in an it configuration task. *Available at SSRN 1130251* (2008).
17. Balkundi, P. & Harrison, D. A. Ties, leaders, and time in teams: Strong inference about network structures effects on team viability and performance. *Academy of Management Journal* **49**, 49–68 (2006).
18. Yang, H.-L. & Tang, J.-H. Team structure and team performance in is development: a social network perspective. *Information & Management* **41**, 335–349 (2004).
19. Guimerà, R., Uzzi, B., Spiro, J. & Amaral, L. A. N. Team assembly mechanisms determine collaboration network structure and team performance. *Science* **308**, 697–702 (2005).
20. Newman, M. E. The structure of scientific collaboration networks. *PNAS* **98**, 404–409 (2001).
21. Aral, S. & Van Alstyne, M. The diversity-bandwidth trade-off. *American Journal of Sociology* **117**, 90–171 (2011).

22. Granovetter, M. S. The strength of weak ties. *American journal of sociology* 1360–1380 (1973).
23. Krackhardt, D. The strength of strong ties: The importance of philos in organizations. *Networks and organizations: Structure, form, and action* **216**, 239 (1992).
24. Ghoshal, S., Korine, H. & Szulanski, G. Interunit communication in multinational corporations. *Management Science* **40**, 96–110 (1994).
25. Hansen, M. T. The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. *Administrative science quarterly* **44**, 82–111 (1999).
26. Peng, M. W. & Luo, Y. Managerial ties and firm performance in a transition economy: The nature of a micro-macro link. *Academy of management journal* **43**, 486–501 (2000).
27. Blansky, D. *et al.* Spread of academic success in a high school social network. *PloS one* **8**, e55944 (2013).
28. Aral, S., Brynjolfsson, E. & Van Alstyne, M. Information, technology and information worker productivity: Task level evidence (2007).
29. Soda, G., Usai, A. & Zaheer, A. Network memory: The influence of past and current networks on performance. *Academy of Management Journal* **47**, 893–906 (2004).
30. Vaquero, L. M. & Cebrian, M. The rich club phenomenon in the classroom. *Scientific reports* **3** (2013).
31. Abbasi, A. & Altmann, J. On the correlation between research performance and social network analysis measures applied to research collaboration networks. In *44th Hawaii International Conference on Systems Science (HICSS-44)*, Jan. 4-7, Hawaii, USA. (2011).
32. Aral, S., Brynjolfsson, E. & Van Alstyne, M. Productivity effects of information diffusion in networks. Available at SSRN 987499 (2007).

33. Harrison, D. A., Mohammed, S., McGrath, J. E., Florey, A. T. & Vanderstoep, S. W. Time matters in team performance: Effects of member familiarity, entrainment, and task discontinuity on speed and quality. *Personnel Psychology* **56**, 633–669 (2003).
34. Ancona, D. G. Outward bound: strategic for team survival in an organization. *Academy of Management Journal* **33**, 334–365 (1990).
35. Levitt, B. & March, J. G. Organizational learning. *Annual Review of Sociology* 319–340 (1988).
36. Wuchty, S. What is a social tie? *PNAS* **106**, 15099–15100 (2009).
37. Kilduff, M. & Tsai, W. *Social networks and organizations* (Sage, 2003).
38. Lincoln, J. R. & Miller, J. Work and friendship ties in organizations: A comparative analysis of relation networks. *Administrative Science Quarterly* 181–199 (1979).
39. Waber, B. N. *et al.* Organizational engineering using sociometric badges. *Available at SSRN* 1073342 (2007).
40. Eagle, N., Pentland, A. S. & Lazer, D. Inferring friendship network structure by using mobile phone data. *PNAS* **106**, 15274–15278 (2009).
41. Rogers, E. M. *Diffusion of innovations* (Simon and Schuster, 2010).
42. Uzzi, B. & Lancaster, R. Relational embeddedness and learning: The case of bank loan managers and their clients. *Management science* **49**, 383–399 (2003).
43. Constant, D., Sproull, L. & Kiesler, S. The kindness of strangers: The usefulness of electronic weak ties for technical advice. *Organization science* **7**, 119–135 (1996).
44. Nelson, R. E. The strength of strong ties: Social networks and intergroup conflict in organizations. *Academy of Management Journal* **32**, 377–401 (1989).
45. Cronbach, L. J. Coefficient alpha and the internal structure of tests. *Psychometrika* **16**, 297–334 (1951).

46. Falchikov, N. Product comparisons and process benefits of collaborative peer group and self assessments. *Assessment and Evaluation in Higher Education* **11**, 146–166 (1986).
47. Kozlowski, S. & Bell, B. chap. Work groups and teams in organizations.
48. Stopczynski, A. *et al.* Measuring large-scale social networks with high resolution. *ArXiv e-prints* (2014). 1401.7233.
49. Rammstedt, B. & John, O. P. Measuring personality in one minute or less: A 10-item short version of the big five inventory in english and german. *Journal of Research in Personality* **41**, 203–212 (2007).
50. Sapiezynski, P. Measuring patterns of human behavior through fixed-location sensors (2013). URL www2.imm.dtu.dk/pubdb/views/edoc_download.php/6556/pdf/imm6556.pdf. (Date of access: 27/03/2014).

APPENDIX D

Smartphones as pocketable labs: Visions for mobile brain imaging and neurofeedback

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Smartphones as pocketable labs: Visions for mobile brain imaging and neurofeedback



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ABSTRACT

Mobile brain imaging solutions, such as the *Smartphone Brain Scanner*, which combines low cost wireless EEG sensors with open source software for real-time neuroimaging, may transform neuroscience experimental paradigms. Normally subject to the physical constraints in labs, neuroscience experimental paradigms can be transformed into dynamic environments allowing for the capturing of brain signals in everyday contexts. Using smartphones or tablets to access text or images may enable experimental design capable of tracing emotional responses when shopping or consuming media, incorporating sensorimotor responses reflecting our actions into brain machine interfaces, and facilitating neurofeedback training over extended periods. Even though the quality of consumer neuroheadsets is still lower than laboratory equipment and susceptible to environmental noise, we show that mobile neuroimaging solutions, like the *Smartphone Brain Scanner*, complemented by 3D reconstruction or source separation techniques may support a range of neuroimaging applications and thus become a valuable addition to high-end neuroimaging solutions.

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1. Introduction

Only recently have wireless neuroheadsets, capable of capturing changing electrical potentials from brain activity through electrodes placed on the scalp using Electroencephalography (EEG), made mobile brain imaging a reality. The emergence of low-cost EEG sensors and the increasing computational power of smartphones may transform neuroimaging from constrained laboratory settings to experimental paradigms, allowing us to model mental state in an everyday context. This presents a paradigm shift, making it possible to design new types of experiments that characterize brain states during natural interaction over extended periods of time. Until recently most neuroimaging experiments have been performed with subjects who are at rest, under the assumption that the brain responses being measured will not be influenced by subjects sitting or laying down. However, this may be inaccurate, as animal studies using mice indicate that neurons in the visual cortex double their visually evoked firing rates if they run on a treadmill rather than stand still (Niel and Stryker, 2010). Since the discovery of parietal–frontal circuits of mirror neurones, which fire both when we grasp an object and when we observe others doing the same (Pellegrino et al., 1992; Gallese et al., 1996), the sensorimotor system can no longer be considered as only involved with motion.

Consequently, these mechanisms should rather be understood as forming an integral part of cognition, allowing us to generalize the goals of actions based on motor representations in the brain (Rizzolatti and Sinigaglia, 2010).

While there is already significant literature concerned with dynamic brain states during natural complex stimuli in conventional laboratory experiments (see e.g., Hasson et al., 2004; Bartels and Zeki, 2004; Dmochowski et al., 2012), there has been a growing call to design studies that relax the constraints of the lab and widen the focus to map out how we perceive our surroundings under naturalistic conditions (Makeig et al., 2009). For example, natural motion has been incorporated into laboratory experiments using tools such as the *MoBi Lab Matlab plugin* (2009) in order to correlate motion capture data of moving limbs with the brain responses being triggered (Gramann et al., 2011). Even adding a few degrees of freedom may provide an understanding of how cortical responses differ by simply changing posture (Slobounov et al., 2008), either by measuring how theta brainwave activity is attenuated in sleepy subjects once they stand up (Caldwell et al., 2003), or by analyzing the modulation in spectral power within alpha and beta brainwaves appearing when one foot hits the ground and the other foot is lifted, as subjects are no longer transfixed on a chair in front of a computer screen (Gwin et al., 2011). This provides a foundation for extending standard EEG paradigms, such as the P300 event-related potential, to measure how we consciously perceive visual objects when participants are no longer required to sit motionless but are able to walk on a belt during the experiment (Gramann et al., 2010). It also makes it

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possible to eventually move a P300 experiment outside the lab, as has recently been demonstrated by Debener and colleagues (2012) by combining the wireless hardware from a consumer neuroheadset¹ with standard EEG cap electrodes² and using a laptop to record the cortical responses, thus providing a portable lab which can be stored in a backpack and easily carried by the subjects participating in the experiment.

Taking the idea of bringing EEG into the wild one step further, the *Smartphone Brain Scanner* (SBS2) open-source software project (<http://github.com/SmartphoneBrainScanner>) introduced in Stopczynski et al. (2011, 2013), makes it possible to build brain imaging applications for real-time 3D source reconstruction or neurofeedback training. By combining a wireless EEG cap with an Android smartphone or tablet, the SBS2 allows for presenting time-locked audiovisual stimuli such as text, images, or video, and it allows for capturing elicited neuroimaging responses on the mobile device, thereby transforming low-cost consumer hardware into a pocketable brain imaging lab. As the *Smartphone Brain Scanner* project potentially allows for designing novel types of brain imaging paradigms, we have initially validated the SBS2 framework in three experiments related to BCI motor control, embodied semantics, and neurofeedback interfaces in order to illustrate the feasibility of capturing mental state in a mobile context. In the following sections we briefly review existing mobile EEG sensors, outline the architectural design of the *Smartphone Brain Scanner* system for real-time 3D reconstruction, describe aspects of source separation and spatial filtering in relation to mobile brain imaging, and give examples of applications built on top of the open-source software framework for mobile Android devices related to imagined finger tapping, emotional responses to text, and design of neurofeedback interfaces (Fig. 1).

2. Mobile EEG acquisition

A wide range of prototype electrode designs, suitable for mobile neuroimaging, are currently under development, based on MEMS microelectromechanical systems utilizing spring-loaded dry contact pins or hard carbon nanotubes that press against the scalp (Ruffini et al., 2008). For long-term EEG measurement without gel, another option is electrodes made from soft foam covered with conductive fabric (Lin et al., 2011), or new types of non-contact high input impedance sensors capable of capturing EEG signals on the basis of capacitive coupling (Chi et al., 2012), even when resting on top of several layers of hair. In contrast to gel-based EEG electrodes, dry contacts need no skin preparation, and can therefore more easily be utilized for neuroimaging as participants are able to put on a neuroheadset without any assistance. However, even though pin or nanotube contacts easily penetrate the hair and therefore offer more possibilities for placement than conductive foam-based sensors attached to the skin of the forehead, a spring-like setup may still be susceptible to noise when users move. Capacitive sensors provide an alternative for unobtrusive physiological monitoring, but require an integrated ultra-high impedance front-end for non-contact biopotential sensing (Chi et al., 2011). So-called Ear-EEG is a promising technology for long-term EEG data collection, offering improved comfort and aesthetics (Looney et al., 2012). Benchmarks of prototype capacitive non-contact and mechanical sensors in an experiment related to decoding a steady state visual evoked potential in the 8–13 Hz frequency band showed only little signal degradation when compared to standard gel-based Ag/AgCl electrodes (Chi et al., 2012), showing that these novel sensors may, in longer term, provide the increased usability that may assure the transformation of neuroimaging from fixed laboratory setups to an everyday mobile context.



Fig. 1. SBS2 mobile EEG recording with real-time 3D source reconstruction, on an Android smartphone connected wirelessly to an Easycap 16 electrode setup based on Emotiv hardware.

Among existing commercial solutions, the ThinkGear module manufactured by NeuroSky³ provides the foundation for several EEG consumer products which integrate a single dry electrode along with a reference and a ground attached to a headband. It provides A/D conversion and amplification of one EEG channel, is capable of capturing brain wave patterns in the 3–100 Hz frequency range, and records at 512 Hz sampling rate. Even a single-channel EEG setup, using a passive dry electrode, such as the NeuroSky, positioned at the forehead and a reference (typically an earlobe), may allow for measuring mental concentration and drowsiness by assessing the relative distribution of brainwave frequencies (Yasui, 2009). More comfortable neuroheadsets using conductive Ni/Cu covered polymer foam, such as Mindo⁴, measure brain activity from the forehead on three EEG electrodes plus a reference channel attached to the earlobe. Integrating analog to digital conversion at 256 Hz sampling rate for acquisition of bandpass filtered signals in the 0.5–50 Hz range, the neuroheadset offers 23 h of battery life and wireless Bluetooth communication, and has been demonstrated in BCI brain machine interfaces used in games based on controlling the power of alpha brainwave activity (Liao et al., 2012). Other consumer neuroheadsets such as the Emotiv EEG, provide both wireless communication via a USB dongle and analog to digital conversion of 16 EEG channels (including reference and ground) at 128 Hz sampling rate while using moist felt-tipped sensors which press against the scalp with a simple spring-like design. Originally designed as a mental game controller capable of tracing emotional responses and facial expressions, the majority of electrodes are placed over the frontal cortex and have no mid-line positions (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 with P3/P4 used as reference and ground). However, as mentioned earlier, Debener and colleagues (2012) recently demonstrated that it is possible to merge the wireless hardware from the Emotiv neuroheadset with high quality, conductive, gel-based electrodes in a standard EEG cap. Repackaging the electronics and battery into a small box (49 mm × 44 mm × 25 mm) which can be attached to the EEG cap and rewired through a connector plug to 16 sintered Ag/AgCl ring electrodes can occur, thus providing a fully customizable montage which allows the electrodes to be freely placed in the EEG cap according to the 10–20 international system (in the present

¹ <http://www.emotiv.com>.

² <http://easycap.de/easycap>.

³ <http://www.neurosky.com/Products/ThinkGearAM.aspx>.

⁴ <http://www.mindo.com.tw/en/index.php>.

experiment Fpz, F3, Fz, F4, C3, Cz, C4, TP9, TP10, P3, Pz, P4, O1, O2 with AFz/FCz used as reference and ground).

We have tested both the original Emotiv neuroheadset as well as the modified EEG cap setup in connection with the *Smartphone Brain Scanner* open-source software project in the experimental designs outlined below.

3. Software framework: Smartphone Brain Scanner

The *Smartphone Brain Scanner* (SBS2) is a software platform for building research and end-user oriented multi-platform EEG applications. The focus of the framework is on mobile devices (smartphones, tablets) and on consumer-grade (low-density and low-cost) mobile neurosystems. SBS2 is freely available under an MIT License at <https://github.com/SmartphoneBrainScanner>. Additional technical details about the framework can be found in Stopczynski et al. (2013).

The framework is divided into three layers: low-level data acquisition, data processing, and applications. The first two layers constitute the core of the system and include common elements used by various applications. The architecture is outlined in Fig. 2.

3.1. Key features

With focus on the mobile devices, SBS2 is a multi-platform framework. The underlying technology – Qt – is an extension of C++ programming language and is currently supported on the main desktop operating systems (Linux, OSX, Windows) as well as mobile devices (Android, BB10, partially iOS) (see <http://qt.digia.com/Product/Supported-Platforms/>).

The additional acquisition and processing modules can be created as C++ classes and integrated directly with the core of the framework. The framework supports building real-time applications; data can be recorded for subsequent offline analysis, most of the implemented data processing blocks aim to provide real-time functionality for working with the EEG signal. The applications developed with SBS2 are applications in the full sense, as they can be installed on desktop and mobile devices, can be started by the user in the usual way, and can be distributed via regular channels, such as repositories and application stores.

The most demanding data processing block is the real-time source reconstruction aimed at producing 3D images as demonstrated in Fig. 4. Source reconstruction is carried out using Bayesian formulation of either the widely used Minimum-norm method (MN) (Hämäläinen and Ilmoniemi, 1994) or the low resolution electromagnetic tomography (LORETA) (Pascual-Marqui et al., 1994). Further description about the

inverse methods implemented in the *Smartphone Brain Scanner* will be given later.

4. Methods

4.1. Brain computer interface based on imagined finger tapping

One of the arguably most widely used paradigms of the brain computer interface literature is a task in which a subject is instructed to select between two or more different imagined movements (Müller-Gerking et al., 1999; Babiloni et al., 2000; Dornhege et al., 2004; Blankertz et al., 2006). Mental imagery is the basis of many BCI systems, originally conceived to assist patients with severe disabilities to communicate by 'thought'. The rationale is that the patient, while having problems carrying out the actual movements, may still be able to plan the movement and thereby produce a stable motor-related brain activity, which can be used as an input to the computer/machine. In this contribution we replicate a classical experiment with imagined finger tapping (left vs. right) inspired by Blankertz et al. (2006). The setup consisted of a set of three different images with instructions, *Relax*, *Left*, and *Right*. In order to minimize the effect of eye movements, the subject was instructed to focus on the center of the screen, where the instructions also appeared (3.5" display size, 800 × 480 pixel resolution, at a distance of 0.5 m) (Fig. 3).

The instructions *Left* and *Right* appeared in random order with an equal probability. A total of 200 trials were conducted for a single subject. We selected 3.5 s duration for the 'active' instruction (*Left* or *Right*) and 1.75–2.25 s randomly selected for the *Relax* task, similar to Blankertz et al. (2006). The main motivation for random duration of the *Relax* task was to minimize the effect of the subject anticipating and starting the task prior to the instruction. The experiment was conducted with an Emotiv EEG neuroheadset transmitting wirelessly to a Nokia N900 smartphone. To illustrate the potential for performing such a study in a completely mobile context, all stimulus delivery and data recording were carried out using the SBS2. Analysis and post-processing and decoding were conducted off-line using standard analysis tools. In particular, we applied a common spatial pattern (CSP) approach (Müller-Gerking et al., 1999) to extract spatial filters which would maximize the variance for one class, while minimizing the variance of the other class and vice versa. A quadratic Bayesian classifier for decoding was applied on features transformed as in Müller-Gerking et al. (1999).

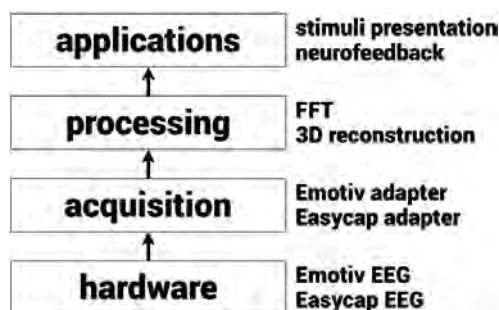


Fig. 2. Layered architecture of the SBS2 framework. Data from connected EEG hardware is extracted by specific adapters, processed, and used by the applications.



Fig. 3. SBS2 mobile neuroimaging apps for neurofeedback training, presentation of experimental stimuli, and real-time 3D source reconstruction, running on Android mobile devices via a wireless connection to an Emotiv or EasyCap EEG setup.



Fig. 4. SBS2 app for presentation of visual stimuli and mobile EEG recording, using an Android tablet connected wirelessly to an EasyCap 16 electrode setup based on Emotiv hardware.

4.2. Source reconstruction and source separation

Compared to standard EEG laboratory setups, mobile neuroimaging is extremely susceptible to noise, as the ability to move around simultaneously introduces artifacts into the neuroimaging data induced by the EEG sensors, as well as originating from motion-related muscle activity. Likewise, mobile neuroimaging is much more exposed to environmental noise than experiments taking place under controlled conditions in a shielded laboratory. Combining sensor and source features, however, has been shown to improve classification in brain-computer interfaces (Ahn et al., 2012), even though these paradigms often involve activation of sensorimotor circuits where the location of sources is already quite well known. There might be an even larger potential by integrating source information for decoding complex brain states involving a range of different cognitive tasks. In particular, spectral analysis of changes in power may offer additional information on activity within specific brain-wave bands, which, based on the frequency, determines whether it reflects local or more distributed cortical field potentials. We therefore suggest that incorporating prior knowledge on what constitutes brain-generated signals may overall enhance the feasibility of performing experiments using mobile neuroimaging solutions (see also Besserve et al., 2011).

One approach to localize the actual brain activity in EEG is to tackle the inverse problem of retrieving the distribution of underlying sources from a scalp map by using a forward head model to estimate the projection weights which are captured by the electrodes. The problem is, however, severely ill-posed, as typically tens of EEG electrodes will capture volume conducted brain activities which may have been generated by tens of thousands of equivalent dipoles representing post-synaptic activity within macrocolumns of the cortex (Hämäläinen and Ilmoniemi, 1994; Pascual-Marqui et al., 1994; Baillet et al., 2001). A regularization that reduces the number of solutions is therefore applied, using methods such as low resolution electromagnetic tomography (LORETA), which assumes both the activity of neighboring neurons is synchronized and their orientation and strength can be modeled as point sources in a 3D grid reflecting 'blurred-localized' images of maximal activity (Pascual-Marqui et al., 1994). With $\mathbf{F} \in \mathbb{R}^{N_e \times N_v}$ representing the forward model relating the N_v cortical current sources, $\mathbf{V} \in \mathbb{R}^{N_e \times N_t}$, to the N_e measured scalp electrodes, $\mathbf{X} \in \mathbb{R}^{N_e \times N_t}$, the forward problem for a set of time points (N_t) is given by, $\mathbf{X} = \mathbf{FV} + \mathbf{E}$, when the noise contribution \mathbf{E} is assumed additive. The Minimum-norm method (MN) (Hämäläinen and Ilmoniemi, 1994) and LORETA methods can be represented as a single method, with MN as a special case of LORETA, namely, when no spatial coherence of neighboring sources is

assumed as prior. From a Bayesian perspective the LORETA method is formulated as

$$p(\mathbf{X}|\mathbf{V}) = \prod_{t=1}^{N_t} \mathcal{N}(\mathbf{x}_t | \mathbf{F}\mathbf{v}_t, \beta^{-1} \mathbf{I}_{N_e}) \quad (1)$$

$$p(\mathbf{V}) = \prod_{t=1}^{N_t} \mathcal{N}(\mathbf{v}_t | 0, \alpha^{-1} \mathbf{L}^T \mathbf{L}) \quad (2)$$

in which β denotes the precision of the noise (inverse variance), α the precision parameter of the sources, and \mathbf{L} the spatial coherence between the sources \mathbf{V} . As the MN method assumes no spatial coherence between neighboring sources, the spatial coherence matrix becomes an identity matrix, $\mathbf{L} = \mathbf{I}$. In contrast, for LORETA this spatial coherence matrix typically takes the form of a graph Laplacian, implementing geometrical neighborhood driven smoothness. Given the likelihood, $p(\mathbf{X}|\mathbf{V})$, and prior distribution, $p(\mathbf{V})$, of the current sources, the most likely source distribution can be obtained by maximizing the posterior distribution over the sources as

$$p(\mathbf{V}|\mathbf{X}) = \prod_{t=1}^{N_t} \mathcal{N}(\mathbf{v}_t | \boldsymbol{\mu}_t, \boldsymbol{\Sigma}_v)$$

$$\boldsymbol{\Sigma}_v = \alpha^{-1} \mathbf{I}_{N_v} - \alpha^{-1} \mathbf{F}^T \boldsymbol{\Sigma}_x \mathbf{F} \alpha^{-1}$$

$$\boldsymbol{\Sigma}_x^{-1} = \alpha^{-1} \mathbf{F} \mathbf{L}^T \mathbf{L} \mathbf{F}^T + \beta^{-1} \mathbf{I}_{N_e} \quad (3)$$

$$\bar{\mathbf{v}}_t = \alpha^{-1} \mathbf{F}^T \boldsymbol{\Sigma}_x \mathbf{x}_t. \quad (4)$$

The hyper-parameters α and β are optimized on-line using a standard Expectation–Maximization (EM) approach (Bishop, 2006).

Rather than aiming to solve the inverse problem of determining the 'what' from 'where' of brain activity, an alternative approach is to apply methods based on higher-order statistics such as independent component analysis (ICA) (Comon, 1994). This allows to separate individual processes ('what') when they stand out as temporally independent in the native, spatially overlapping scalp representation (Makeig et al., 1996).

The ability of ICA to identify temporally independent events also allows for enhanced detection and automatic removal of artifacts (Delorme et al.). Eye blinks manifest themselves as low 1–3 Hz as well as higher frequency activity, which translates into stereotypical ICA scalp maps consisting of a single frontal dipole (Delorme et al., 2007). When comparing this method against a regression approach using an electrooculogram (EOG) eye movement correction procedure (EMCP) to remove eye blink artifacts, ICA turns out to yield almost perfect correction (Hoffmann and Falkenstein, 2008). Also, other kinds of muscle activity stand out distinctly in the corresponding scalp maps. Overall, applying ICA as a preprocessing step improves artifact detection compared to analysis based on the raw EEG data (Delorme et al., 2007). With particular relevance to mobile neuroimaging, it has been demonstrated that independent component-based gait-artifact removal makes it possible to capture neural correlates in standard EEG experiments, even when walking or running (Gwin et al., 2010).

EEG experiments have traditionally focused on analysis of event-related time-domain waveform deflections and frequency-domain perturbations in power, but neither of these approaches fully captures the underlying brain dynamics when averaging data over multiple trials, or ignoring phase resetting that contributes to the ERP (Makeig et al., 2004). When first applying ICA to the EEG data, the event-related time series waveforms come to represent independent components generated by temporally independent, physiologically decoupled local field potentials, and their corresponding scalp maps that resemble dipolar projections of the underlying sources (Delorme et al., 2012). This indicates that ICA may be used for more than denoising, e.g., it can

be used to find the modes of event-related changes in power, as the independent components framed by the dimensions of frequency, power, and phase consistency across trials. Even when electrodes are accurately placed, the recorded potentials may still vary due to individual differences in cortical surface and volume conduction. ICA may also here provide a common framework for comparison of the underlying brain activity in EEG data, regardless of the actual electrode positions. We thus compared ICA of the EEG data retrieved from both the Emotiv neuroheadset containing no central electrodes and the Easycap EEG montage including midline electrodes. In particular, we used the retrieved scalp maps and activation time series, as well as event-related changes in power spectra, to perform a statistical group comparison across experimental conditions and trials. As a preprocessing step, we reduced dimensionality based on principal component analysis (PCA) and subsequently applied K-means clustering to the independent components, in order to identify common patterns of brain activity across the two different mobile EEG setups (Delorme et al., 2011).

4.3. Visual stimulus to investigate emotional responses

Over the past decades, neuroimaging studies have established that language is grounded in sensorimotor areas of the brain; highly related neuronal circuits seem involved whether we literally pick up a ball or in a phrase refer to grasping an idea (Pulvermüller and Fadiga, 2010). Exploring whether such brain activation can be detected using a mobile EEG setup, the SBS2 framework was used to display the stimulus consisting of a subset of action verbs related to emotional expressions, face, and hand motion as used in a recent fMRI experiment (Moseley et al., 2011). The framework was also used to record the EEG signal for subsequent offline data analysis.

Two mobile 16 channel EEG setups were compared; the low cost Emotiv neuroheadset using saline sensors positioned laterally at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4 (P3/P4 used as Common Mode Sense (CMS) reference/Driven Right Leg (DRL) feedback) – versus a standard electrolyte gel-based EEG cap (Easycap, Germany) similar to what has previously been used for mobile P300 experiments (Debener et al., 2012) enabling an EEG setup including central and midline Ag/AgCl ring electrodes positioned at Fpz, F3, Fz, F4, C3, Cz, C4, TP9, TP10, P3, Pz, P4, O1 and O2 (AFz/FCz used as CMS reference/DRL feedback) according to the international 10–20 system.

A single subject pilot study was performed to compare the Emotiv and Easycap EEG setups based on 2×10 trials, each consisting of 3×20 action verbs presented in a randomized sequence on the smartphone display (Nokia N900). Each verb was exposed for 1000 ms in a large white font on black background ($3.5''$ display size, 800×480 pixel resolution) at a distance of 0.5 m, preceded by a fixation cross 500 ms pre-stimuli, and followed by 1000 ms post-stimuli black screen. Using the EEGLAB plug-in for MATLAB (MathWorks, USA), epoched EEG data was extracted offline (-500 ms to 1000 ms) and baseline corrected (-500 ms to 0 ms). As some of the recorded potentials are induced by muscle activity, we rejected abnormal data epochs by specifying that the spectrum should not deviate from baseline by ± 50 dB at $0-2$ Hz and manually removed eye blinks (Delorme et al., 2011). To facilitate a comparison between the different electrode placements used in the two experiments, we applied the extended Infomax algorithm to linearly project the EEG data recorded from individual electrodes onto a space of basis vectors, which were temporally independent from each other, using independent component analysis ICA to estimate the scalp maps and time courses of individual neural sources (Delorme et al., 2007).

To assess the degree to which the Emotiv neuroheadset and the Easycap EEG setups capture common patterns in brain activity despite their differences in electrode montage, rather than simply measuring event-related responses from the 14 electrodes, we applied ICA in a single-subject study to retrieve 14 independent components from each of the 2×10 trials, related to the Emotiv and Easycap experiments, respectively: we analyzed $2 \times 10 \times 14$ independent components

generated from the time-locked responses to reading 3×20 emotion, face, and hand-related action verbs in each trial. Retrieving the ICA components enabled us to initially compare the event related responses across the 3 action verb conditions, which in turn enabled us to identify similar independent sources within trials using the EEGLAB studyset functionality. Secondly, to identify common patterns of brain activity both within and across the Emotiv and Easycap experiments, the EEGLAB studyset functionality and MATLAB Statistical Toolbox were used to cluster the $2 \times 10 \times 14$, in total 280 ICs based on scalp maps, power spectra, and amplitude time series. After initially applying ICA for artifact rejection in each trial, the 280 ICA weights were recomputed as a basis for a statistical analysis using the EEGLAB studyset functionality (Delorme et al., 2011), where the dimensionality of the feature space was reduced to $N = 10$ by applying PCA principal component analysis (Jolliffe, 2002). The pre-clustering function PCA compresses the multivariate EEG features into a smaller number of mutually uncorrelated scalp projections, and computes a vector for each component to define normalized distances in a subspace representing the largest covariances in the ICA-weighted data. This means that the vectors contain the 10 highest PCA components for the ICA-weighted time series responses, scalp maps, and power, related to the three conditions. Next, the K-means algorithm ($K = 10$) was applied to cluster common ICA components within the 10 trials ($\sigma = 3$), related to the Emotiv neuroheadset (Fig. 13) and the Easycap EEG setup (Fig. 14), respectively. Comparing functionally equivalent groups of ICs makes it possible to assess whether they resemble recurring neural sources retrieved from multiple sessions, and to determine if the clustered ICs remain shared across the two different experimental EEG setups (Fig. 5).

4.4. Mobile interfaces for neurofeedback

In contrast to personal informatics apps, neurofeedback interfaces require the user to interact in real time with audiovisual representations of EEG data in an attempt to control the ongoing brain activity. Neurofeedback experiments aiming to increase power in the upper alpha range have been shown to improve cognitive performance in several studies (Hanslmayr et al., 2005; Zoefel et al., 2011). While there is often a peak in individual alpha brainwave power around 10 Hz, neurofeedback training makes it possible to control and shift the activity towards the upper alpha range of 12 Hz. In relation to neurofeedback, an ability to consciously control alpha brainwave oscillations, which as a gating mechanism appears to be involved in selective attention (Foxe and Snyder, 2011), might thus potentially help explain the previously reported training effects on cognitive performance. Likewise, an association between higher alpha frequency and good memory performance has previously been shown (Klimesch, 1999) (Fig. 6).

However, designs for neurofeedback interfaces are often conceptualized with little attention to how the actual feedback of audiovisual elements might affect the user's ability to control brain activity. Normally, User Experience (UX) design of graphical interfaces involves initial modeling of user needs and selection of design patterns for organizing content and navigational layout reflecting gestalt principles. This may

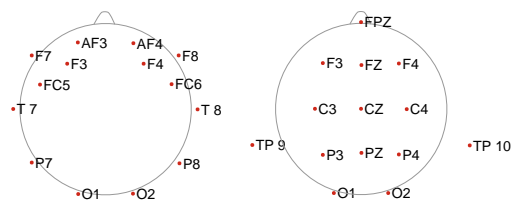


Fig. 5. Electrode locations for two mobile 16 channel EEG setups; the Emotiv neuroheadset using saline sensors positioned laterally (left), versus a standard gel-based Easycap EEG montage including central and midline positions (right).



Fig. 6. SBS2 neurofeedback training app running on an Android tablet, where a blue to orange shift in color horizontally over time represents an increase in upper alpha power.

subsequently be translated into frameworks for interaction ranging from scrollable timeline lists to multilayered contextual map metaphors (Tidwell, 2011). Neurofeedback applications on the other hand have typically concentrated on mapping EEG amplitude values directly onto audiovisual components. For example, sounds of ocean waves or high- or low-pitched gongs (Egner et al., 2004; Hinterberger et al., 2004) would map to visual designs based on vertical scales and squares of changing colors (Zoefel et al., 2011; Neumann et al., 2003; Vernon et al., 2003). When targeted towards children, these elements have been incorporated into more complex scenarios built around airplanes, a 3D car racing environment, or a pole-vaulting cartoon mouse (Gevensleben et al., 2009; Heinrich et al., 2007). In summary, these designs may be understood as based on contrasting combinations of the following audiovisual components (Jensen et al., 2013):

- pitch (low, high)
- volume (soft, loud)
- timbre (dark, light)
- duration (short, long)
- rhythm (temporal distribution)
- geometric primitives (connected segments)
- color (discrete, gradients)
- size (proximity, scalability)
- movement (horizontal, vertical)
- composition (spatial distribution).

To explore the influence that such components might have on the efficacy of neurofeedback training, we tested two different interfaces developed for the SBS2. We conducted an experiment with 25 subjects aiming at increasing their upper alpha frequency band (Jensen et al., 2012). The neurofeedback experiment consisted of two iterations, testing the two different interfaces. In the first iteration, 12 healthy subjects (7 males and 5 females) with an average age of 23.6 ± 1.9 did neurofeedback training on a replication of an existing interface (Zoefel et al., 2011). This interface indicated brain activity based on only two components (color gradients framed by a square primitive). In the second iteration another 13 healthy subjects (7 male and 6 female) with an average age of 26.6 ± 5.5 performed neurofeedback training using an interface developed on basis of the common features extracted from the first group of subjects. The second interface combined four components (scaled down

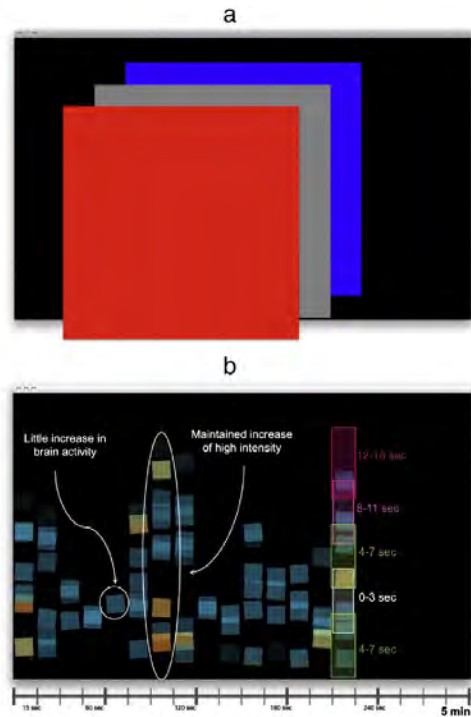


Fig. 7. (a) In the interface from the first version of the neurofeedback application, the current brain activity is visualized by the square changing colors; blue indicating activity below, gray – equal to, and red – above baseline. (b) The interface of the neurofeedback application from the second iteration is shown with additional illustrations describing how it is constructed: The 5-minute timeline shown in the bottom illustrates how the training session is divided into columns of 15 s. Within a column squares would appear first (0–3 s) in a window in the lower part of the screen, then (4–7 s) in windows above and below the first window and lastly (8–11 s and 12–15 s) in windows above the first two windows. The windows are shown in the rightmost column which was not shown during the experiments. The encircled column illustrates how the user can easily compare the ability to increase brain activity in different time intervals.

color gradients framed by square primitives spatially distributed horizontally and vertically).

The EEG signal from all of Emotiv's 16 electrodes was recorded and the real-time feedback was constructed from O1 and O2. Additionally, an offline re-referencing of P3 and P4 with the frontal electrodes AF3, AF4, F3 and F4 allowed for P3 and P4 to be included in the later data processing, thus covering a larger area of the relevant cortical area. The power of the brain activity was calculated using Fast Fourier Transformation.

Both iterations consisted of five sessions during one week from Monday to Friday. Each session started and ended with a 5-minute baseline recording measuring the average brain activity during a simple task. In between the baseline recordings five 5-minute training sessions were conducted. After each session, we gathered qualitative data on the thought patterns of the subjects leading to an increase of alpha brain activity based on informal interviews. Each subject received a total of 25 training recordings and 10 baseline recordings.

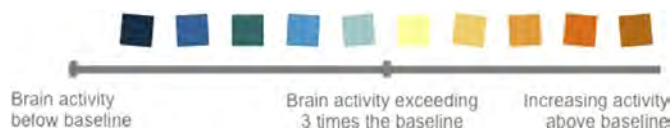


Fig. 8. The colors of the squares indicate the intensity of the brain activity.

The interface used in the first iteration was similar to the one used in a study by Zoefel et al. (2011), where the feedback consisted of a square of changing colors gradually from blue, gray to red. Respectively each color represented real-time amplitudes below, equal to baseline, or above baseline, respectively, see Fig. 7a. The subjects were instructed to make the square turn red. For the baseline recording a similar interface setup was used but with random color changes, making the visual stimuli similar to those of the training recordings and therefore more compatible. The subjects were asked to count the number of times the square turned red. This would ensure a similar cognitive task across the subjects while recording the baseline, thereby making these recordings comparable.

The feedback interface used in the second iteration consisted of small squares being generated once a second, if the alpha amplitudes exceeded the baseline. Over a 15 second interval the squares (maximum 15 squares) were assembled into a column, after which a new column of squares was incrementally generated along a horizontal axis. At the end of the 5 minute training recording, the interface would consist of 20 columns of squares, see Fig. 7b. Thus the interface not only showed the current amplitudes, but also the previous, allowing the user to easily compare methods for increasing the amplitudes. The squares not only indicated when the amplitudes exceed baseline, but also the degree of increase by a change in color, ranging from dark blue to orange (see Fig. 8). The degree of increase was calculated from a running mean creating a smooth color flow. The subjects were instructed to create as many squares as possible and preferably with yellow and orange colors. For the baseline recording a similar interface was used, although with squares appearing randomly in the columns and with random color. The subjects were asked to count the yellow and orange squares.

All subjects of both iterations were asked to keep their eyes open for as long as possible, and avoid muscle movements, jaw movements, and swallowing during all recordings to limit artifacts.

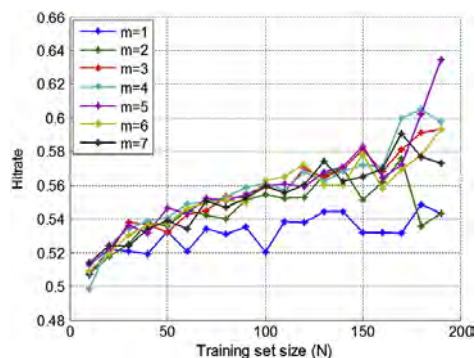


Fig. 9. Mean accuracy of left and right imagined finger tapping classification for a single subject. Mean accuracy is based on 200 splits in training and test data. Classification is based on CSP and a quadratic Bayes classifier focusing on bandpass filtered data 8–32 Hz in interval 0.75–2.00 s after onset.

5. Results and discussion

In this section we present the results of the experiments, validating the performance of the software, platforms used, and EEG hardware.

5.1. Brain computer interface based on imagined finger tapping

In order to validate the applicability of the platform in decoding imagined left and right finger tapping, the EEG data was bandpass filtered (8–32 Hz) and we used the data in the interval 0.75–2.00 s after stimuli onset as input to the common spatial pattern (CSP) algorithm (Müller-Gerking et al., 1999). One important parameter in the CSP algorithm to be controlled is the number of spatial filters. To determine the number of spatial filters we applied cross-validation and examined the performance (accuracy of classifier) as a function of the training size (number of trials used for training), see Fig. 9. The classifier was trained on a balanced set of trials (i.e. equal number of left and right trials), which was carried out 200 times for each training set size.

Fig. 9 indicates that we need more than a single spatial filter ($m > 1$). When $m = 2$, for example, two spatial filters are used to maximize the variance for class 1 while minimizing the variance for class 2 and an additional two spatial filters are used to minimize the variance for class 1 while maximizing the variance for class 2. It is interesting that only a few spatial filters are required to obtain an accuracy close to 60%. We also note that performance is increasing as a function of samples, hence, even better performance can be expected if more samples are collected.

5.1.1. Source reconstruction and source separation

For further validation we applied standard statistical evaluation for significance and correction for multiple comparisons. Thus, we performed a Monte Carlo permutation test (Maris and Oostenveld, 2007) to check for significant electrode differences between left and right finger tapping. Fig. 10 demonstrates a scalp map of the effect of the averaged response based on left finger tapping minus averaged response based on right finger tapping. The significant channels at given time intervals are highlighted in accordance with the Monte Carlo permutation test conducted using Fieldtrip (Oostenveld et al., 2011). Both positive and negative effects are detected as significant with Monte Carlo p -values of 0.012 and 0.001, respectively. A set of 1000 random permutations were performed. Inspecting Fig. 10 reveals significant differences over the left and the right hemisphere and more importantly the electrodes contributing to the significant difference between left and right imagined finger tapping are electrodes located close to the premotor area. Thus, it seems that these electrodes are taking over the often reported electrodes C3 and C4 as the main drivers, as C3 and C4 are not present in the Emotiv EEG sensor configuration.

To examine the ability to perform reliable 3D EEG imaging based on the data acquired using an Emotiv neuroheadset, source reconstruction was carried out on the bandpass-filtered imagined finger tapping data (8–32 Hz) also used for the classification task and in the non-parametric statistical test. Fig. 11 illustrates the mean power of the difference between left and right imagined finger tapping in the interval 0.75–2.00 s post-stimuli. Premotor areas are typically involved in executing the task and in differentiating a left from right imagined movement. This is also the case here to some extent with minor

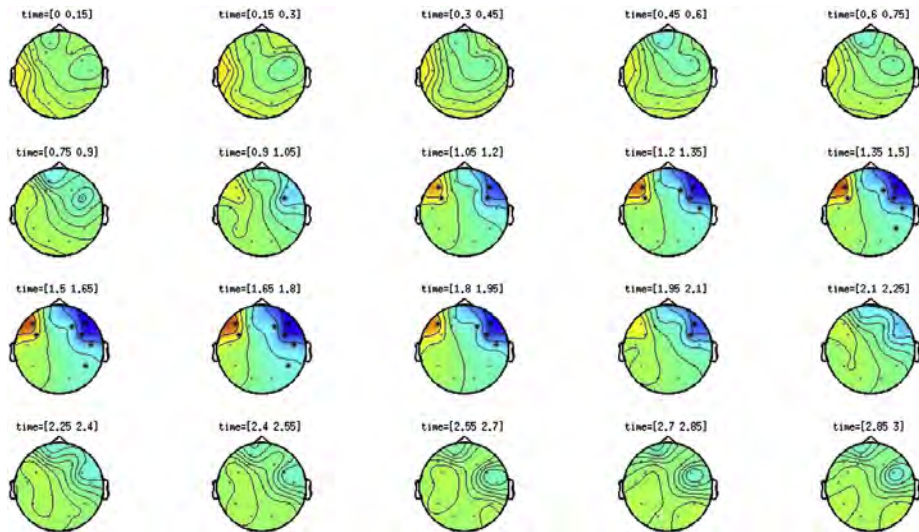


Fig. 10. Monte Carlo permutation test for significant difference between averaged left imagined finger tapping response and averaged right imagined tapping. Electrodes located close to the premotor region are detected as significant in the time interval 0.9–2.1 s after stimuli.

discrimination in the premotor areas and more pronounced discrimination in the more frontally located areas. Note the polarity of the power difference map, with the left hemisphere indicating a positive difference and the right hemisphere indicating a negative contribution. During the imagined finger tapping part, the contralateral premotor/motor regions desynchronize (resulting in a decrease in power within the specific frequency range) while the ipsilateral premotor/motor regions first desynchronize shortly and right after synchronize (meaning increased power within the frequency range). The main explanation for the displacement more frontally found in Fig. 11,

is the uneven distribution of sensors for the Emotiv EPOC system, with most of the sensors positioned frontally.

However, large proportions of the occipital and temporal areas are also found to be active by the reconstruction. These apparent visual and temporal source activation differences may, however, be explained by the fact that re-referencing to an average channel is performed prior to source estimation. Since the distribution of the sensor locations is highly unevenly distributed, with the majority placed frontally, re-referencing data with a strong frontal activation (e.g. eye blink/movement) to an average reference channel will map part of the

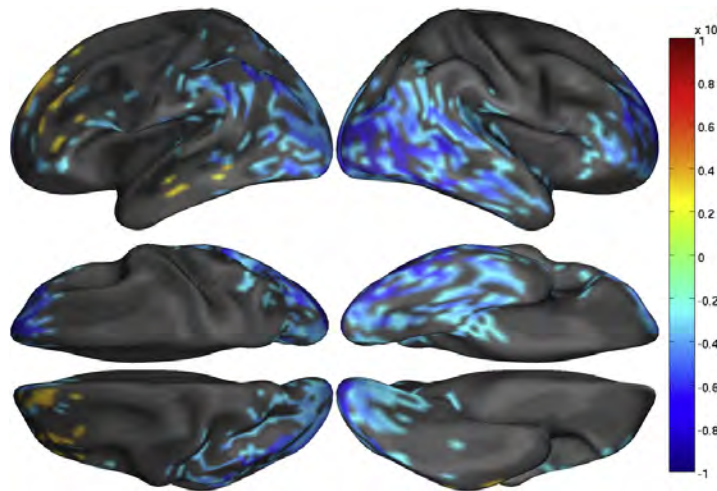


Fig. 11. Source reconstruction of mean difference power map between left and right imagined finger tapping.

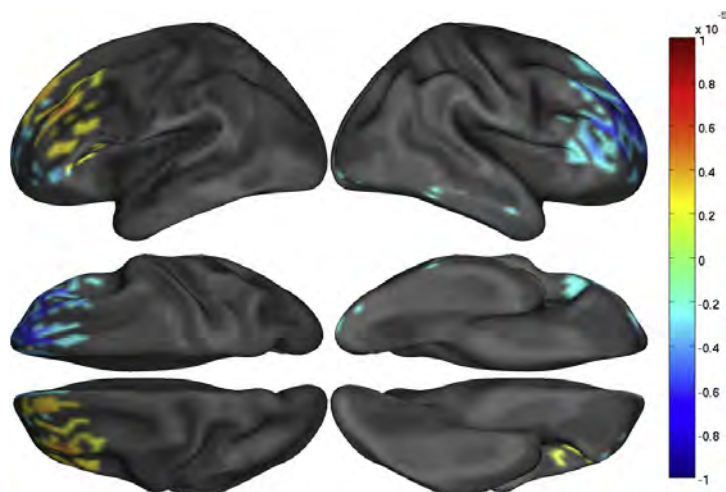


Fig. 12. Source reconstruction of mean difference power map between left and right imagined finger tapping. Emotiv EEG data corrected by removal of ICA component associated with eye movement.

frontal activity to the temporal and occipital electrodes. To further test this hypothesis, we investigated the influence of artifacts caused by eye motion on the source reconstruction estimates by removing an eye-related ICA component. Indeed, the removal of the eye movement component seems to improve the source estimates significantly, as demonstrated in Fig. 13. The operating regions (frontal areas and slightly pre-motor regions) are more highly visible in this power difference map between the averaged left minus right imagined finger tapping conditions. Similarly, as in Fig. 11, the sources are displaced more frontally than typically, and this can be explained by the sensor positioning offered by the Emotiv EPOC system. The source reconstruction was performed offline to ensure a fair comparison with and without removal of the ICA component related to eye movement. The ICA decomposition was performed using the extended Infomax algorithm supported by EEGLAB (Fig. 12).

5.2. Visual stimulus to investigate emotional responses

Within the Emotiv data, 2×18 ICs have been clustered in 10 out of 10 trials, indicating that these independent components are consistently activated across all trials (Fig. 13). Similarly, in the Easycap data, 23 ICs have been clustered within 3 standard deviations of the K-means centroids in 10 out of 10 trials, while 9 ICs have been grouped in 7 out of 10 trials, confirming that temporally independent activations are also grouped across trials in this study (Fig. 14). Taking the relative

polarity of ICs into account when comparing the two studies, the clustered scalp maps in both experiments suggest left lateralized prefrontal as well as parietal activations in language areas, which integrate motor and semantic aspects connected through the dorsal and ventral streams in the brain (Rolheiser et al., 2011; Axer et al., 2012).

This is in line with results obtained in a recent MRI experiment (Moseley et al., 2011) using the same verbs as in the present EEG study, indicating that premotor neural circuits are activated when passively reading verbs related to face and hand motion and when seeing emotional expressions. Mobile neuroimaging could potentially extend our ability to explore such action-based links between actual motion and emotion in an everyday context, which might in turn reflect imitation of gestures or facial expressions involving mirror neuron circuits in the brain, possibly providing a foundation for higher level feelings of empathy and theory of mind.

5.3. Mobile interfaces for neurofeedback

All signal processing of the data for the Neurofeedback experiment was done off-line using the EEGLAB (Delorme and Makeig, 2004) plug-in for MATLAB.

Since the alpha frequency band has shown to vary depending on age, possible neurological diseases, and memory performance (Klimesch, 1999), the upper alpha frequency band had to be determined for each individual. By identifying the peak in the power spectrum, the

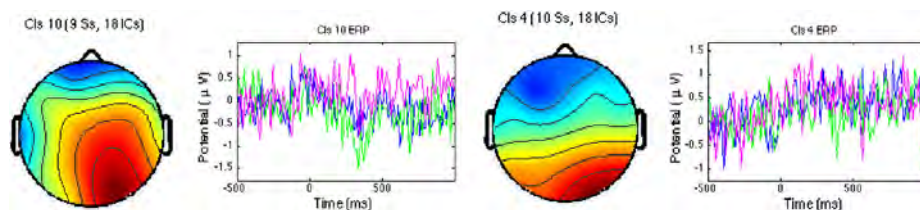


Fig. 13. Single-subject EEG neuroimaging study with Emotiv 16 channel neuroheadset: PCA dimensionality reduction and K-means clustering ($K = 10$, $\sigma = 3$) of 140 IC scalp maps, activation time series and event-related changes in power spectra based on 10 trials, each consisting of reading 3×20 emotion (blue), face (green) and hand (pink) related action verbs.

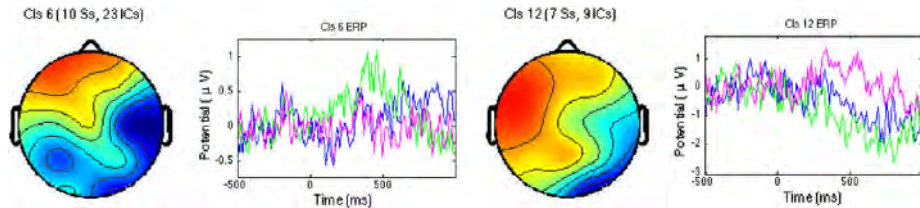


Fig. 14. Single-subject EEG neuroimaging study with Easycap 16 channel EEG setup: PCA dimensionality reduction and K-means clustering ($K = 10$, $\sigma = 3$) of 140 IC scalp maps, activation time series and event-related changes in power spectra based on 10 trials, each consisting of reading 3×20 emotion (blue), face (green) and hand (pink) related action verbs.

individual alpha peak (IAF), the upper alpha frequency band was set as a band of 2 Hz above IAF (from IAF to IAF + 2Hz). Thus the individuals' upper alpha frequency band were determined from the first baseline recording of every session, and the mean amplitude was calculated for all baseline and training recordings. Two subjects (1 male and 1 female) from the first iteration of the experiment did not complete all training sessions, and were therefore excluded from further analysis.

In addition, it has repeatedly been reported that some subjects, usually called non-responders, are unable to change amplitudes of the brain frequencies significantly (Zoefel et al., 2011; Gevensleben et al., 2009; Fuchs et al., 2003; Lubar et al., 1995). Subjects who did not show a significant increase in the upper alpha frequencies when comparing the very first baseline (baseline 1 in session 1) with the training recordings from Friday (session 5) were considered non-responders. As a result, 3 subjects (2 female, 1 male) from the first iteration and another 3 subjects (2 male, 1 female) from the second iteration were considered non-responders. These left 7 subjects in the first iteration (5 male, 2 female) and 10 subjects in the second iteration (5 male, 5 female) remain for statistical analysis.

The individuals' EEG results from the baseline- and training recordings were normalized in respect to the first baseline Monday (session 1), thereby showing the ability to increase upper alpha (UA) amplitudes in relation to the first baseline in percentage. The results obtained over the week (Monday to Friday) have been plotted in Fig. 15. Each

line represents a subject's ability to increase UA amplitudes: The red lines represent subjects from the first iteration, the black lines represent subjects from the second iteration and the bold lines represent the non-responders. From the graph it is clear that some subjects are more capable of increasing their UA amplitudes and increase above 400%, whereas others experience a decrease (usually the non-responders). In addition, the subjects who get the highest increase are mainly those who use the second iteration interface. However, the variance in the subject ability to increase their UA is also greater.

These results suggest that the ability to control neural activity is very individual and that the interface should be supportive of the individual's strategies.

Following the approach of Zoefel et al. (2011), we fitted regression lines to the individual UA amplitudes as a function of session number (1–35) and used a one-sample, one-sided *t*-test to test whether they were significantly greater than zero, which they were in both iterations ($p < 0.05$ and $p < 0.03$ for the first and second iterations respectively). We also compared the regression lines between the iterations using a two-sample, two-sided *t*-test and found no significant difference ($p > 0.70$). This result, in itself, could indicate that the two types of feedback are equally effective.

This approach does not, however, separate the effect of training (a lasting increase in UA amplitude) from the feedback effect (an immediate increase in UA amplitude during feedback). To isolate the training

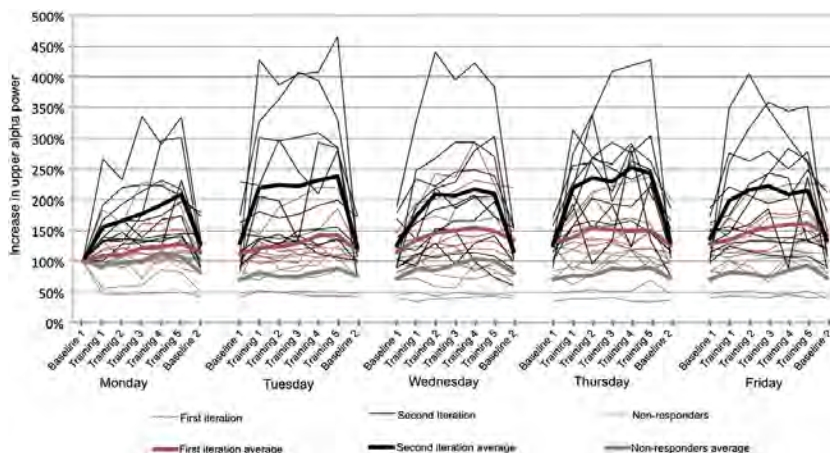


Fig. 15. The individuals' upper alpha (UA) amplitude in percentage of the UA amplitude from the first baseline recording on the first day (Monday). Subjects from first and second iterations as well as the non-responders from both iterations are plotted in red, black and gray, respectively. The average of these groups is marked by bold lines in corresponding colors. All baseline- and training recordings have been plotted in sequence across the week, e.g. Monday will show results from the first baseline, then the 5 training recordings, ending with the second baseline, giving a total of 7 points of each day. The results illustrate a large variance in the individual subjects ability to increase UA amplitudes, where subjects from the second iteration were capable of reaching a greater increase, although some subjects were unable to achieve any increase at all (referred to as non-responders).

effect, we again follow the approach of Zoefel et al. who quantified the training effect as the difference between UA amplitude during the first baseline recording in the first session and the first baseline recording in the last session and tested for an increase with a one-sample one-sided *t*-test. Using this approach we found a significant effect in the first iteration ($p < 0.002$) but not in the second iteration ($p > 0.14$). This result indicates that the interface used in the first iteration was more effective for neurofeedback training.

In addition to this, we are also interested in isolating the feedback effect, which we quantify as the difference between the mean UA amplitude across feedback recordings and the mean UA amplitude across the first and last baseline recording for each session. We compare the feedback effect from the two iterations using a repeated-measures ANOVA with session number as within subject factor and iteration as between groups factor. We found a significant effect of iteration ($F(1,15) = 11.85, p < 0.005$) but no significant effect of session number or the interaction between session and iteration. Based on the lack of effect of the session number, we averaged the feedback effect across session number and subjects within an iteration and found that the mean feedback effect was 0.17 for the first iteration and 0.67 for the second iteration. This result indicates that the interface used in the second iteration was more effective for inducing an immediate increase in UA amplitude.

That the feedback effect was higher in the second group without a corresponding increase in the training effect suggests that the magnitude of UA amplitude during feedback does not completely determine the training effect. This could be due to a ceiling effect, so that UA amplitude during training has no effect above a certain level. Alternatively, it could also mean that the two groups used different strategies for increasing UA amplitude during training and that although the second group's strategy was more efficient for increasing UA amplitude during feedback, it did not increase the training effect. Such strategic differences could be facilitated by the difference in the visual feedback stimulus. In the first group participants needed to constantly look at the feedback stimulus to get feedback, whereas the second group could look elsewhere intermittently and return their gaze to the feedback stimulus only when they wished to learn about their performance. This could change the UA amplitude during feedback without increasing the training effect as could the mere physical differences in the feedback signals.

In summary, our neurofeedback study confirms the findings of Zoefel et al. (2011), provides new insights into the effects of the type of feedback provided, and confirms that neurofeedback training is possible with a mobile setup based on the *Smartphone Brain Scanner*.

6. Further perspectives

6.1. Hardware

Current consumer-grade and research-oriented mobile EEG systems are only the first iteration of the hardware. We predict two major directions of the development.

On one hand, the high-density systems will become mobile, pushing for the best possible quality of the acquired signal in naturalistic conditions. The development of these systems will not be primarily focused on making them unobtrusive, fashionable, or consumer-operated. From the spectrum of the features offered by the new EEG hardware, these systems will focus on mobility, portability, and low-cost. They will be used in the more or less classical experiments, controlled and initiated by the researchers.

On the other hand, more consumer-oriented devices will emerge. They will be fitted for particular use-cases, which will allow to make them smaller, concealed, and user-friendly. Such sensors will not necessarily be seen as EEG devices, but rather as cognitive state monitoring devices, and in addition to the EEG signal, they may include other electro-physiological signals, such as EMG, ECG, and skin conductance.

Still, the data available from a large number of such systems bought and worn by the consumers for their particular function, may offer an unparalleled opportunity for understanding human brain and cognitive states. Gaining privacy-preserving access to, and analyzing noisy, not-at-all or poorly annotated data originating from brain state, from hundreds or thousands of subjects and collected over days, weeks, or months can become one of the grand challenges for cognitive neuroscience in the next few years.

The development of neuroheadsets and sensors accompanies the development of mobile devices, smartphones and tablets, allowing for personal hubs for interconnected, wearable devices. The increasing processing power and low-energy protocols (e.g., Bluetooth 4.0, NFC) turn our personal space into a busy network of devices (phones, Bluetooth headsets, smart watches, glasses, hearing aids etc.). EEG sensors, even if equipped with a single electrode, can fit naturally in such systems, as long as they can provide certain well-defined value for the user.

6.2. Software

The evolution of the software will be closely coupled with the use-cases of the hardware solutions. For the research-focused high-density mobile hardware, the minimal requirement of data collection and possibly transmission on mobile devices can be easily satisfied with simple software. In such cases, the already existing frameworks, such as EEGLAB, can utilize significant processing power of desktop or even server systems, and can even be used for data processing and transmitting the extracted features back to the user.

For more consumer-oriented sensors, real-time applications, possibly operating directly on mobile devices without server connection, need to be developed. The *Smartphone Brain Scanner* is the first framework that enables such development; pushing the limits of what can be done in terms of creating user value by enabling novel EEG applications. As the mobile devices performing the processing grow more powerful, more complex algorithms can be enabled to compensate for noise and low density of the systems.

6.3. Experiments

The vast majority of studies of neural and cognitive functions have so far been set in the laboratory, where the subject is severely restrained in movement, isolated from the surrounding world, and is required to carry out the same limited task repeatedly. This is an impoverished environment that we normally live in and are optimized to function in; it totally ignores human agency.

Taking EEG out of the laboratory and into the natural world will allow us to move beyond these constraints. Measuring the EEG of a freely moving subject will allow us to characterize the neural activity of many important functions. With wearable EEG we can study natural motion such as walking and complex composite motion. We can also study the many cognitive tasks that we constantly perform in their full complexity. Examples include preference-based choice as we select given consumer goods over others, the constant updating of working memory throughout our daily work, and the use of speech in natural social interactions. Measuring the EEG of subjects in rich natural environments will allow us to characterize the neural function of the perceptual systems when they are met with rich multimodal stimuli in which attention is constantly needed to select the relevant stimuli and filter out irrelevant stimuli.

The complexity and variability of data collected in the natural environment will be tremendous compared to the data collected in the laboratory. In order to derive anything meaningful from it, the amount of necessary data will be equally tremendous. Wearable EEG offers an immediate solution as hours, days, even weeks of data can be collected outside of the laboratory; something which is completely unrealistic in lab-based experimentation.

7. Conclusions

Mobile brain imaging, here realized as an EEG system, offers huge promise for many research areas. Here we show our initial work with the *Smartphone Brain Scanner* framework, which can record, analyze, and 3D real-time visualize EEG signals directly on a mobile device, using low-cost, consumer-grade neuroheadsets. The signal obtained in the studies, although of low dimensionality (14 channels) and noisy, can still be successfully used for multiple classical neuroscience applications, including brain-computer interfaces (BCIs), analysis of high-level brain activity, and neurofeedback. The features of the presented system make it possible to use in domains such as cognitive psychology, medical applications, social science research, as well as for “self monitoring” as promoted by the Quantified Self community⁵.

As the presented framework runs on mobile devices, including tablets and smartphones, it can be coupled with other embedded sensors in a natural way. In this sense, EEG serves as an extension of the sensing capabilities of the already existing devices, and can be used in an integrated way with the other collected data (e.g. location, social interactions, activity level).

We argue that the presented framework enables a wide variety of experiments, and the initial set of these presented in this paper serves as a validation and showcase of the versatility of the framework and general approach. It is now clear that we are at the stage where hardware is powerful and inexpensive enough to be used for mobile brain imaging, while at the same time available algorithms can handle noisy data, allowing us to recover significant information.

The approach to user-oriented and mobile EEG does not end with the notion of researchers using the mobile devices and consumer-grade neuroheadsets to collect the data from the subjects. We can easily imagine that the systems will eventually be able to deliver interesting data to the public, giving them incentive to invest in their own hardware. In this shift, the data would be collected and uploaded by the participants themselves, distributing the cost and difficulty of running experiments. This presents yet more challenges, such as data quality control and privacy. On the other hand, it does give a promise of extremely large datasets created for large populations and over long periods of time, for only little costs.

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References

- Ahn, M., Hong, J.H., Jun, S.C., 2012. Feasibility of approaches combining sensor and source features in brain-computer interface. *J. Neurosci. Methods* 204, 168–178.
- Axer, H., Klingner, C.M., Prescher, A., 2012. Fiber anatomy of dorsal and ventral language streams. *Brain Lang.* <http://dx.doi.org/10.1016/j.bandl.2012.04.015>.
- Babiloni, F., Cincotti, F., Lazzarini, L., Millan, J., Mourino, J., Varsta, M., Heikonen, J., Bianchi, L., Marciani, M., 2000. Linear classification of low-resolution EEG patterns produced by imagined hand movements. *IEEE Trans. Rehabil. Eng.* 8, 186–188.
- Baillet, S., Mosher, J., Leahy, R., 2001. Electromagnetic brain mapping. *IEEE Signal Proc. Mag.* 18, 14–30.
- Bartels, A., Zeki, S., 2004. Functional brain mapping during free viewing of natural scenes. *Hum. Brain Mapp.* 21, 75–85.
- Besserve, M., Martinerie, J., Garnero, L., 2011. Improving quantification of functional networks with EEG inverse problem: evidence from a decoding point of view. *Neuroimage* 55, 1536–1547.
- Bishop, C.M., 2006. *Pattern Recognition and Machine Learning*. Springer, NY 10013 (USA).
- Blankertz, B., Dornhege, G., Krauledat, M., Müller, K., Kunzmann, V., Losch, F., Curio, G., 2006. The Berlin brain-computer interface: EEG-based communication without subject training. *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 147–152.
- Caldwell, J.A., Przinko, B., Caldwell, J.L., 2003. Body posture affects electroencephalographic activity and psychomotor vigilance task performance in sleep-deprived subjects. *Clin. Neurophysiol.* 114, 23–31.
- Chi, Y.M., Maier, C., Cauwenberghs, G., 2011. Integrated ultra-high impedance front-end for noncontact biopotential sensing. *Biomedical Circuits and Systems Conference, 2011. BioCAS 2011*, Xplore, IEEE.
- Chi, Y., Wang, Y.-T., Wang, Y., Maier, C., Jung, T.-P., Cauwenberghs, G., 2012. Dry and noncontact EEG sensors for mobile brain-computer interfaces. *IEEE Trans. Neural Syst. Rehabil. Eng.* 20, 228–235.
- Comon, P., 1994. Independent component analysis, a new concept? *Signal Process.* 36, 287–314.
- Debener, S., Minow, F., Emkes, R., Gandras, K., Vos, M., 2012. How about taking a low-cost, small, and wireless EEG for a walk? *Psychophysiology* 49, 11, 1617–1621.
- Delorme, A., Makeig, S., 2004. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J. Neurosci. Methods* 134, 9–21.
- Delorme, A., Sejnowski, T.J., Makeig, S., 2007. Enhanced detection of artifacts from EEG data using higher-order statistics and independent component analysis. *Neuroimage* 34.
- Delorme, A., Mullen, T., Kothe, A., Acar, Z., Bigdely-Shamlo, N., Vankov, A., Makeig, S., 2011. EEGLAB, SIFT, NIFT, BCILAB, and ERICA: new tools for advanced EEG processing. *Comput. Intell. Neurosci.* 2011, 10.
- Delorme, A., Palmer, J., Onton, J., Oostenveld, R., Makeig, S., 2012. Independent EEG sources are dipolar. *PLoS One* 7. <http://dx.doi.org/10.1371/journal.pone.0030135>.
- Delorme, A., Makeig, S., Sejnowski, T., 2001. Automatic artifact rejection for EEG data using high-order statistics and independent component analysis. *International workshop on ICA (San Diego, CA)*.
- Dmochowski, J.P., Sajda, P., Dias, J., Parra, L.C., 2012. Correlated components of ongoing EEG point to emotionally laden attention—a possible marker of engagement? *Front. Hum. Neurosci.* 6.
- Dornhege, G., Blankertz, B., Curio, G., Müller, K., 2004. Boosting bit rates in non-invasive EEG single-trial classifications by feature combination and multi-class paradigms. *IEEE Trans. Biomed. Eng.* 51 (6), 993–1002.
- Egner, T., Zech, T.F., Gruzelier, J.H., 2004. The effects of neurofeedback training on the spectral topography of the electroencephalogram. *Clin. Neurophysiol.* 115, 2452–2460.
- Foxe, J.J., Snyder, A.C., 2011. The role of alpha-band brain oscillations as a sensory suppression mechanism during selective attention. *Front. Psychol.* 2, 1–13.
- Fuchs, T., Birbaumer, N., Lutzenberger, W., Gruzelier, J.H., Kaiser, J., 2003. Neurofeedback treatment for attention-deficit/hyperactivity disorder in children: a comparison with methylphenidate. *Appl. Psychophysiol. Biofeedback* 28, 1–12.
- Gallese, V., Fadiga, L., Fogassi, L., Rizzolatti, G., 1996. Action recognition in the premotor cortex. *Brain* 119, 593–609.
- Gevensleben, H., Holl, B., Albrecht, B., Vogel, C., Schlamp, D., Kratz, O., Studer, P., Rothenberger, A., Moll, G.H., Heinrich, H., 2009. Is neurofeedback an efficacious treatment for ADHD? A randomised controlled clinical trial. *J. Child Psychol. Psychiatry* 50, 780–789.
- Gramann, K., Gwin, J.T., Bigdely-Shamlo, N., Ferris, D.P., Makeig, S., 2010. Visual evoked responses during standing and walking. *Front. Hum. Neurosci.* <http://dx.doi.org/10.3389/fnhum.2010.00202>.
- Gramann, K., Gwin, J.T., Ferris, D., Die, K., Jung, T., Lin, C., Liao, L., Makeig, S., 2011. Cognition in action: imaging brain/body dynamics in mobile humans. *Rev. Neurosci.* 22, 593–608.
- Gwin, J.T., Gramann, K., Makeig, S., Ferris, D.P., 2010. Removal of movement artifact from high-density EEG recorded during walking and running. *J. Neurophysiol.* <http://dx.doi.org/10.1152/jn.01005.2010>.
- Gwin, J.T., Gramann, K., Makeig, S., Ferris, D.P., 2011. Electroocutaneous activity is coupled to gait cycle phase during treadmill walking. *Neuroimage* 54.
- Hämäläinen, M., Ilmoniemi, R., 1994. Interpreting magnetic fields of the brain: minimum norm estimates. *Med. Biol. Eng. Comput.* 32, 35–42.
- Hanslmayr, S., Sauseng, P., Doppelmayr, M., Schaubus, M., Klimesch, W., 2005. Increasing individual upper alpha power by neurofeedback improves cognitive performance in human subjects. *Appl. Psychophysiol. Biofeedback* 30. <http://dx.doi.org/10.1007/s10484-005-2169-8>.
- Hasson, U., Nir, Y., Levy, I., Fuhrmann, G., Malach, R., 2004. Intersubject synchronization of cortical activity during natural vision. *Science* 303, 1634–1640.
- Heinrich, H., Gevensleben, H., Strehl, U., 2007. Annotation: neurofeedback – train your brain to train behaviour. *J. Child Psychol. Psychiatry* 48, 3–16.
- Hinterberger, T., Neumann, N., Pharn, M., Kübler, A., Grether, A., Hofmayer, N., Wilhelm, B., Flor, H., Birbaumer, N., 2004. A multimodal brain-based feedback and communication system. *Exp. Brain Res.* 154, 521–526.
- Hoffmann, S., Falkenstein, M., 2008. The correction of eye blink artefacts in the EEG: a comparison of two prominent methods. *PLoS One* 3. <http://dx.doi.org/10.1371/journal.pone.0003004>.
- Jensen, C., Birgitte, F., et al., 2012. Training your brain on a tablet. 34th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).
- Jensen, C., Birgitte, F., et al., 2013. Spatio temporal media components for neurofeedback. 2013 IEEE International Conference on Multimedia and Expo (ICME).
- Jolliffe, I.T., 2002. *Principal Component Analysis*. Springer Series in Statistics, 1986. Springer.
- Klimesch, W., 1999. EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain Res. Brain Res. Rev.* 29, 169–195.
- Liao, L.-d., Chen, C.-Y., Wang, I.-J., Chen, S.-F., Li, S.-Y., Chen, B.-W., Chang, J.-Y., Lin, C.-T., 2012. Gaming control using a wearable and wireless EEG based brain computer interface device with novel dry foam based sensors. *J. Neuroeng. Rehabil.* 9 (<http://www.jneuroengrehab.com/content/9/1/5>).
- Lin, C.-T., Liao, L.-d., Liu, Y.-H., Wang, I.-J., Lin, B.-S., Chang, J.-Y., 2011. Novel dry polymer foam electrodes for long-term EEG measurement. *IEEE Trans. Biomed. Eng.* 58, 1200–1207.
- Looney, D., Kidmore, P., Park, C., Ungstrup, M., Rank, M.L., Rosenkranz, K., Mantic, D.P., 2012. The in-the-ear recording concept: user-centered and wearable brain monitoring. *IEEE Pulse* 3, 32–42.

⁵ <http://quantifiedself.com/>.

Smartphones as pocketable labs: Visions for mobile brain imaging and neurofeedback

180

66

A. Stopczynski et al. / International Journal of Psychophysiology 91 (2014) 54–66

- Lubar, J.F., Swartwood, M.O., Swartwood, J.N., O'Donnell, P.H., 1995. Evaluation of the effectiveness of EEG neurofeedback training for ADHD in a clinical setting as measured by changes in T.O.V.A. scores, behavioral ratings, and WISC-R performance. *Biofeedback Self Regul.* 20, 83–99.
- Makeig, S., Bell, A.J., Jung, T.-P., Sejnowski, T.J., 1996. Independent component analysis of electroencephalographic data. *Adv. Neural Inf. Process. Syst.* 8, 145–151.
- Makeig, S., Debener, S., Onton, J., Delorme, A., 2004. Mining event-related brain dynamics. *Trends Cogn. Sci.* 8, 204–210.
- Makeig, S., Gramann, K., Jung, T., Sejnowski, T., Poizner, H., 2009. Linking brain, mind and behavior. *Int. J. Psychophysiol.* 73, 95–100.
- Maris, E., Oostenveld, R., 2007. Nonparametric statistical testing of EEG-and MEG-data. *J. Neurosci. Methods* 164, 177–190.
- MoBi Lab Matlab plugin, 2009. http://sccn.ucsd.edu/wiki/MoBi_Lab (Accessed: 2013-02-27).
- Moseley, R., Carota, F., Hauk, O., Mohr, B., Pulvermüller, F., 2011. A role for the motor system in binding abstract emotional meaning. *Cereb. Cortex* 1–14. <http://dx.doi.org/10.1093/cercor/bhr238>.
- Müller-Gerking, J., Pfurtscheller, G., Flyvbjerg, H., 1999. Designing optimal spatial filters for single-trial EEG classification in a movement task. *Clin. Neurophysiol.* 110, 787–798.
- Neumann, N., Kübler, A., Kaiser, J., Hinterberger, T., Birbaumer, N., 2003. Conscious perception of brain states: mental strategies for brain-computer communication. *Neuropsychologia* 41, 1028–1036.
- Niel, C.M., Stryker, M.P., 2010. Modulation of visual responses by behavioral state in mouse visual cortex. *Neuron* 65, 472–479.
- Oostenveld, R., Fries, P., Maris, E., Schoffelen, J., 2011. Fieldtrip: open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Comput. Intell. Neurosci.* 2011, 1.
- Pascual-Marqui, R.D., Michel, C.M., Lehmann, D., 1994. Low resolution electromagnetic tomography: a new method for localizing electrical activity in the brain. *Int. J. Psychophysiol.* 18, 49–65.
- Pellegrino, G.d., Fadiga, L., Fogassi, L., Gallese, V., Rizzolatti, G., 1992. Understanding motor events: a neurophysiological study. *Exp. Brain Res.* 91, 176–180.
- Pulvermüller, F., Fadiga, L., 2010. Active perception: sensorimotor circuits as a cortical basis for language. *Nat. Neurosci.* 11, 351–360.
- Rizzolatti, G., Sinigaglia, C., 2010. The functional role of the parieto-frontal mirror circuit: interpretations and misinterpretations. *Nature* 11, 264–274.
- Rolheiser, T., Stamatakis, E.A., Tyler, L.K., 2011. Dynamic processing in the human language system: synergy between the arcuate fascicle and extreme capsule. *J. Neurosci.* 31, 16949–16957.
- Ruffini, G., Dunne, S., Fuenteterrilla, L., Grau, C., Farrés, E., Marco-Pallarés, J., Watts, P.J.P., Silva, S.R.P., 2008. First human trials of a dry electrophysiology sensor using a carbon nanotube array interface. *Sensors Actuators A Phys.* 144, 275–279.
- Slobounov, S., Hallett, M., Cao, C., Newell, K., 2008. Modulation of cortical activity as a result of voluntary postural sway direction: an EEG study. *Neurosci. Lett.* 442. <http://dx.doi.org/10.1016/j.neulet.2008.07.021>.
- Stopczynski, A., Larsen, J.E., Stahlhut, C., Petersen, M.K., Hansen, L.K., 2011. A smartphone interface for a wireless EEG headset with real-time 3D reconstruction. *Affective Computing and Intelligent Interaction*. Springer, pp. 317–318.
- Stopczynski, A., Stahlhut, C., Larsen, J.E., Petersen, M.K., Hansen, L.K., 2013. The smartphone brain scanner: a mobile real-time neuroimaging system. <http://arxiv.org/abs/1304.0357>.
- Tidwell, J., 2011. Designing Interfaces – Patterns for Effective Interaction Design. O'Reilly.
- Vernon, D., Egner, T., Cooper, N., Compton, T., Neilands, C., Sheri, A., Gruzelić, J.H., 2003. The effect of training distinct neurofeedback protocols on aspects of cognitive performance. *Int. J. Psychophysiol.* 47, 75–85.
- Yasui, Y., 2009. A brainwave signal measurement and data processing technique for daily life applications. *J. Physiol. Anthropol.* 28, 145–150.
- Zoefel, B., Huster, R.J., Herrmann, C.S., 2011. Neurofeedback training of the upper alpha frequency band in EEG improves cognitive performance. *Neuroimage* 54, 1427–1431.

APPENDIX E

Smartphones get emotional: mind reading images and reconstructing the neural sources

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Smartphones get emotional: mind reading images and reconstructing the neural sources

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Abstract. Combining a 14 channel neuroheadset with a smartphone to capture and process brain imaging data, we demonstrate the ability to distinguish among emotional responses reflected in different scalp potentials when viewing pleasant and unpleasant pictures compared to neutral content. Clustering independent components across subjects we are able to remove artifacts and identify common sources of synchronous brain activity, consistent with earlier findings based on conventional EEG equipment. Applying a Bayesian approach to reconstruct the neural sources not only facilitates differentiation of emotional responses but may also provide an intuitive interface for interacting with a 3D rendered model of brain activity. Integrating a wireless EEG set with a smartphone thus offers completely new opportunities for modeling the mental state of users as well as providing a basis for novel bio-feedback applications.

Keywords: affective computing, mobile EEG, ICA clustering, source reconstruction

1 Motivation

Consciousness and emotion are not separable. Cognitively speaking our feelings can be thought of as labels that we consciously assign to the emotional responses triggered by what we perceive [1]. While we often think of affective terms as describing widely different states, these can be represented as related components in a circumplex model framed by the two psychological primitives: valence and arousal [2]. Related to viewing affective pictures, earlier neuroimaging studies have established that emotional content trigger not only autonomic responses of increased heart rate and electrodermal skin conductance, but also distinct brain potentials characterizing pleasant or unpleasant feelings compared to neutral imagery [3]. These ERP responses covary with both autonomic arousal and self report [4], and have been validated by affective user ratings in the IAPS set of affective pictures, using the psychological dimensions of valence and arousal to define how pleasant or intense the emotional content is perceived as being [5]. Previous brain imaging studies of emotional responses when viewing affective pictures [4] have identified distinct differences in the ERP amplitudes elicited

by pleasant and unpleasant compared to neutral images. An early component emerge most pronounced for pleasant content at 150-200ms termed early posterior negativity EPN, triggering a relative negative shift over temporal occipital areas and a positive potential over central sites [6]. Followed by yet another ERP component; a late positive potential LPP at 300-500ms, characterized by an enhanced posterior positivity over central parietal sites for affective compared to neutral content, with left hemisphere enhanced for pleasant pictures while activation appeared right lateralized for unpleasant images [3].

Only recently affordable wireless EEG headsets, initially designed as cognitive game interfaces have become available, and subsequently been applied as brain machine interfaces to directly manipulate robotic arms [7], drive a car [8] or mentally select images using the P300 oddball paradigm to call contacts by mentally selecting their image from the phonebook of an iPhone [9]. Scott Makeig et al. [10] have summarized the many benefits of brain monitoring under naturalistic conditions, emphasizing the need for going beyond brain imaging paradigms gauging how a few bits of information move through the brain when tapping a finger, and widen the focus to map out how we actively perceive our surroundings in a mobile context reflected in embodied cognition and real life emotional responses. However the obvious question remains whether the limited number of electrodes and the quality of consumer priced EEG sets make it feasible to capture brain imaging data in noisy environments. We therefore decided to combine a wireless neuroheadset with a smartphone for presenting media, gauge the emotional responses by capturing the EEG data and subsequently process and visualize the reconstructed patterns of brain activity on the device. And in the following sections outline the mobile EEG system design, experimental setup, results based on ICA analysis and source reconstruction, which are discussed in relation to earlier neuroimaging findings obtained in laboratory settings using conventional EEG equipment.

2 Methods

2.1 Mobile EEG system

The Neuroheadset transmits the EEG and control data to a receiver module with a standard USB connector, originally intended for a Windows PC running the Emotiv research edition SDK. We instead connect the receiver module directly to the USB port on a Nokia N900 smartphone, running Maemo 5. The current version is designed as a client-server architecture so that computationally expensive data analysis can be performed on a remote server and results are transmitted back to the phone for presentation. For synchronizing the stimuli with the captured EEG data, we timestamp the beginning and end of the recording when the first and last packets arrive. Meaning, the theoretical 128 Hz sample rate turns out to be 126-127 Hz when averaged over several minutes of recording. The timestamps saved during the experiments indicate that a resolution of 10 msec is achieved with the current Python implementation.

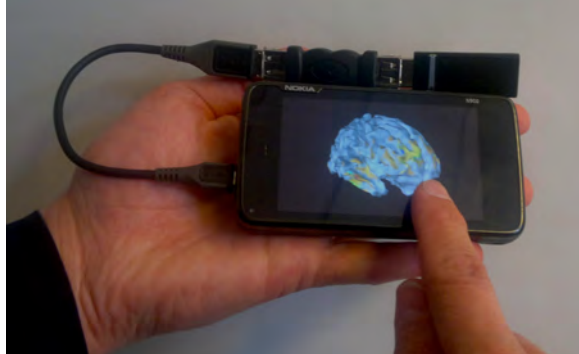


Fig. 1. The wireless 14 channel neuroheadset transmits the brain imaging data via a receiver connected directly to the USB port on a Nokia N900 smartphone, using components and custom-made software in order to transfer the received EEG data to a server for further processing. The present implementation allows interaction with a reconstructed 3D model of brain activity by mapping touch display movements to rotation in one dimension.

2.2 Experimental setup

Eight male volunteers from the Technical University of Denmark, between the ages of 26 and 53 (mean age 32,75 years) participated in the experiment. Replicating the setup for identifying neural correlates of emotional responses triggered by affective pictures, originally performed using a high density 129 electrode array [3], we in the present study applied a simplified approach based on a portable wireless Emotiv Research Edition 14 channel neuroheadset (<http://emotiv.com>) to capture the signal from Ag/AgCl electrodes positioned at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 according to the international 10-20 system. Channels were recorded at a sampling rate of 128Hz. using the electrodes P3/P4 as CMS reference and DRL feedback respectively. Based on earlier studies showing that late emotional responses to affective pictures remain unaffected when varying the size of images [11], the participants viewed a randomized sequence of 60 IAPS images presented on the 3.5" display (800 x 480 screen resolution) of N900 Nokia smartphones rather than on a standard monitor. Combining earlier experimental designs for eliciting emotional responses when viewing affective pictures, we selected 3 x 20 images from the user rated international affective picture system IAPS [5] identical to the subset used in [3] representing categories of pleasant (erotic and family photos) unpleasant (mutilated bodies, snakes and spiders) and neutral images (simple objects as well non-expressive portraits of people). Taking into consideration findings establishing that the ERP neural correlates of affective content in images can be distinguished even when

the exposure of target pictures are limited to 120ms [6], we opted for adopting the experimental picture viewing paradigm outlined in [12], where a randomized sequence of images from the 3 x 20 IAPS picture categories are presented with 0.5 second prestimulus consisting of a white fixation cross on black background, before a 1 second visual stimulus presentation of a picture followed by a subsequent 1 second poststimulus black screen.

2.3 ICA data analysis

While the rows of the matrix of EEG data initially consist of voltage differences measured over time between each electrode and the reference channel, they come to represent temporally independent events that are spatially filtered from the channel data by applying ICA independent component analysis [13]. Even though neither the location of electrodes or aspects of volume conductance in the brain are part of the equation, the ICA decomposition of the original data matrix often results in independent components resembling scalp projections of brain dipoles, as they reflect synchronous brain activity of local field potentials projected through volume conduction throughout the scalp [14]. However part of the recorded potentials are induced by eye movement, muscle activity and noise and we followed the approach in [15] to cluster ICA components retrieved from each subject to remove the artifacts and isolate the components representing information sources based on the EEGLAB plug-in (v9.0.4.4) for Matlab (R2010b). Initially by reducing the dimensionality of the feature space to $N=10$ by applying PCA principal component analysis [16], which as a pre-clustering function computes a vector for each component to define normalized distances in a subspace representing the largest covariances within scalp maps and power spectra. Subsequently, we applied a Kmeans algorithm choosing $K=10$ to cluster similar ICA components and separate outliers that remain more than three standard deviations removed from any cluster centroids. After clustering the 8 x 14 ICA components generated from the continuous EEG trial data of each subject, we after visual inspection of averaged scalp topographies and power spectra manually removed 5 of the 10 clusters, containing spatially localized components like eye artifacts or independent components resembling muscle activity characterized by high power spectra at high frequencies.

2.4 Source reconstruction

The inverse problem of estimating the distribution of underlying sources from a scalp map is severely ill-posed with multiple solutions, as the electrodes are placed at a distance and therefore sum the volume conducted brain activities from cortical areas throughout the scalp [15]. We note that apart from providing a relevant neurofeedback signal it has been argued that a sparse 3D representation may in fact also improve decoding [17]. The forward propagation is linear and written in terms of a matrix A , relating the measured electrode signals $Y = AX + E$ to the sought source signals X where E is a noise term [18]. The forward model depends on sensor positions based on a head model of

the spatial distribution of tissue and conductivity values. Assuming the noise to be time independent Gaussian distributed, the observation model becomes $p(y_t|x_t, \Sigma_E) = N(y_t|Ax_t, \Sigma_E)$ where Σ_E is the noise spatial covariance matrix. We here apply a Bayesian formulation of the widely used minimum norm (MN) method for solving the inverse problem [19]. The MN method allows for fast computation of the inverse solution. In a MN setting a multivariate Gaussian prior for the sources with zero mean and covariance $\alpha^{-1}I_{N_d}$ is assumed. Moreover, it is assumed that the forward propagation model is fixed and known. With Bayes rule the posterior distribution is maximized by

$$\Sigma_y = (\alpha^{-1}AA^T + \beta^{-1}I_{N_c})^{-1} \quad (1)$$

$$\hat{X} = \alpha^{-1}A^T\Sigma_yY \quad (2)$$

where the hyper parameters, α and β are estimated online using a Bayesian EM approach.

3 Results

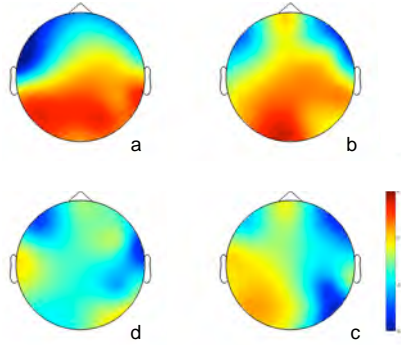


Fig. 2. Mobile EEG event related potentials ERP averaged across eight subjects at 300-500ms after stimuli in the 8-12 Hz frequency band, captured by a 14 channel wireless neuroheadset when viewing affective images on the 3.5" display of a smartphone depicting: a) pleasant - erotic couples b) unpleasant - mutilated bodies c) neutral people and d) household objects. Compared to earlier neuroimaging findings based on the same paradigm but using high density 129 electrode EEG equipment in a laboratory setting [3] [6] we obtain similar results indicating: overall increased posterior activation for a) pleasant and b) unpleasant compared to c) neutral people and d) objects, as well as increased activation in parietal cortex for a) pleasant versus b) unpleasant content.

6 M.K. Petersen, C. Stahlhut, A. Stopczynski, J.E. Larsen and L.K. Hansen

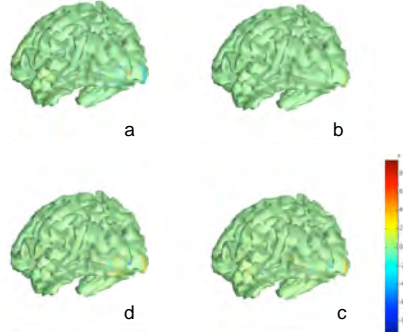


Fig. 3. Activation at 172ms after picture onset in the 8-12Hz frequency band may represent the 150-200ms early posterior negativity EPN previously observed [3] [6] based on reconstruction of sources generated from scalp maps averaged across eight subjects viewing: a) pleasant b) unpleasant c) neutral people and d) objects. Consistent with earlier neuroimaging findings, the reconstructed sources reflect increased activity in the 150-200ms time window for a) pleasant versus b) unpleasant, whereas the differences between pleasant a) versus c) and d) neutral content appear less significant.

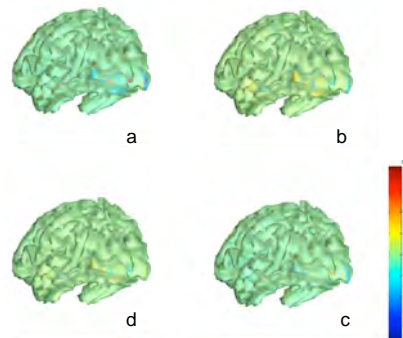


Fig. 4. Activation at 422ms after picture onset in the 8-12Hz frequency band may represent the 300-500ms late posterior positivity LPP previously observed [3] [6] based on reconstruction of sources generated from scalp maps averaged across eight subjects viewing: a) pleasant b) unpleasant c) neutral people and d) objects. Consistent with earlier neuroimaging findings, the reconstructed sources reflect increased activity and polarity reversals in the 300-500ms time window for a) pleasant versus b) unpleasant, and increased activity for affective versus c) and d) neutral content.

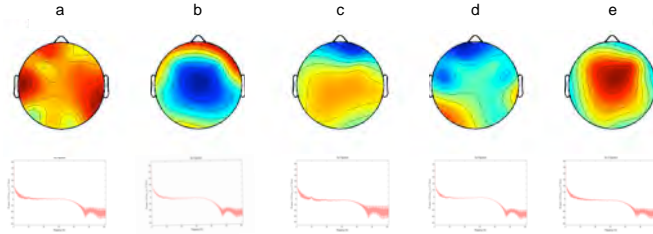


Fig. 5. Clusters of scalp maps and associated power spectra generated from continuous mobile EEG trial data from eight subjects, by applying a kmeans algorithm to 8×14 temporally independent ICA independent components represented in a 10 dimensional subspace reduced by PCA principal component analysis. While the clustered ICA components do not represent absolute scalp map polarities as such, they indicate common sources of synchronous brain activity in the 8-12 Hz frequency band, consistent with activities in central, temporal and parietal cortex previously observed to differentiate responses when viewing affective pictures compared to neutral content [3] [6].

4 Discussion

Combining a 14 channel neuroheadset with a smartphone for capture and processing of brain imaging data, our findings indicate we can distinguish among emotional responses reflected in different scalp potentials when viewing pleasant and unpleasant pictures and thereby replicate results previously obtained using conventional high density 129 electrode EEG equipment [3] [6]. Analyzing the event related potentials ERP averaged across eight subjects at 300-500ms after stimuli in the 8-12 Hz frequency band when viewing affective images (Fig.2), we find overall increased posterior activation for pleasant and unpleasant pictures compared to neutral people and objects, as well as increased activation in parietal cortex for pleasant versus unpleasant content. Illustrating how varying emotional intensity in the 300-500ms time window after presentation of emotional content draws attention and defines a selective processing making it possible to distinguish among the feelings triggered when consuming media in a real life setting.

Even though the neuroheadset has only a limited number of channels and no central electrodes, its inclusion of positions F7/F8, P7/P8 and O1/O2 are likely essential for the obtained results, as these electrodes have earlier been shown to contribute significantly to the differentiation between affective and neutral pictures using conventional EEG equipment [3]. Raising the question as to whether the electrode positions can be considered similar, as the form factor of the neuroheadset will provide a slightly different fit for each subject depending on the shape of the head in contrast to traditional EEG caps. However, even when

electrodes are accurately placed the recorded potentials may still vary due to individual differences in cortical surface and volume conduction. We therefore clustered the 8 x 14 ICA components generated from continuous EEG trial data in order to identify common patterns of brain activity across the eight subjects. Among the clusters retained after artifact removal (Fig.5), 39 ICA components clustered in b) and d) were shared by all eight subjects, the 18 ICA components within clusters a) and e) by five subjects, while c) was related to 7 ICA components found in three subjects. Indicating an ability to consistently capture common patterns of brain activity across subjects even when taking into account the less accurate positioning and limited number of electrodes. While the clustered ICA components do not represent absolute scalp map polarities as such, they indicate common sources of synchronous brain activity in the 8-12 Hz frequency band, consistent with activities in central, temporal and parietal cortex previously observed to differentiate responses when viewing affective pictures compared to neutral content [3] [6].

Going beyond analysis of averaged ERPs and clustering of ICA components, we took a Bayesian approach to learn the parameters for applying the minimum norm (MN) method and thus reconstruct the underlying sources from the recorded scalp potentials. Initially exploring the 150-200ms time window an activation at 172ms after picture onset in the 8-12Hz frequency band may represent the early posterior negativity EPN previously observed [3] [6] here based on reconstruction of sources generated from scalp maps averaged across eight subjects viewing: a) pleasant b) unpleasant c) neutral people and d) objects. Consistent with earlier neuroimaging findings, the reconstructed sources reflect increased activity in the 150-200ms time window for pleasant versus unpleasant, whereas the differences between pleasant versus neutral content appear less significant. This early component thought to reflect direction of attentional resources has earlier been found to be more significant for pleasant relative to neutral content, and source reconstruction may thus potentially provide additional features for differentiating among positive and negative content. Within the 300-500ms time window we found a maximal activation at 422ms after picture onset which based on the reconstructed sources may represent the late posterior positivity LPP previously observed using a conventional EEG setup [3] [6]. It has been suggested that the LPP component reflects increased allocation of neural resources for processing emotionally salient relative to neutral content, which here appear activated in the left parietal cortex for pleasant versus unpleasant, and increased activity for affective versus neutral content. Applying a Bayesian formulation to reconstruct the underlying neural sources may thus provide additional information that not only adds to the differentiation of emotional responses captured in a mobile EEG setting, but may also provide an intuitive interface for interacting with a 3D rendered model of brain activity as a basis for developing novel bio-feedback applications. (Fig.1).

The early and late components are not limited to differentiating among the stark emotional contrasts characterizing images selected from the IAPS collection [5]. Whether we read a word with affective connotations, come across some-

thing similar in an image or recognize from the facial expression that somebody looks sad, the electrophysical patterns reflecting the connections among neural populations in the brain seem to suggest that the underlying emotional processes might be the same [20]. Reflecting that we are constantly attracted to or avoiding sensations related to traces in memories capturing pleasure and pain of past experiences, that as feelings are conceptualized as bodily states integral to establishing our sense of self [21]. Using fMRI imaging in experiments to trace which parts of the brain are involved when people read emotional words, the results indicate that activation in two distinct neural networks are linearly correlated with the values of valence or arousal [22]. Overall the valence network linking prefrontal areas and the amygdala are activated in a reciprocal manner whenever the emotional balance shifts from positive to negative, suggesting a feedback loop that moderate our feelings in order for them not to grow out of bounds. Whereas the amount of arousal in words are positively correlated with increased neural activity in a circuit involving the cingulate cortices and the hippocampus linked to prefrontal areas that might again provide an inhibiting effect on arousal. Meaning that the our responses to the emotional content we come across in images or words as measured in the IAPS [5] and ANEW [23] user rated values framed by the dimensions of valence and arousal, might literally correspond to actual neural processes in the brain pertaining to two distinct networks. The ability to continuously capture these patterns by integrating wireless EEG sets with smartphones for runtime processing of brain imaging data may offer completely new opportunities for modeling the mental state of users in real life scenarios as well as providing a basis for novel bio-feedback applications.

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References

1. Antonio Damasio, "Feelings of emotion and the self," *Annals of the New York Academy of Sciences*, vol. 1001, pp. 253–261, 2003.
2. James A. Russell, "A circumplex model of affect," *Journal of Personality and social psychology*, vol. 39, no. 6, pp. 1161–1178, 1980.
3. Andreas Keil, Margaret M. Bradley, Olaf Hauk, Brigitte Rockstroh, Thomas Elbert, and Peter J. Lang, "Large-scale neural correlates of affective picture processing," *Psychophysiology*, vol. 39, pp. 641–649, 2002.
4. Bruce N. Cuthbert, Harld T. Schupp, Margaret M. Bradley, Niels Birbaumer, and Peter J. Lang, "Brain potentials in affective picture processing: covariation with autonomic arousal and affective report," *Biological Psychology*, vol. 52, pp. 95–111, 2000.
5. Peter J. Lang, Margaret M. Bradley, and Bruce N. Cuthbert, "International affective picture system (iaps): Affective ratings of pictures and instruction manual," Tech. Rep. A-8, University of Florida, Gainesville, FL, 2008.
6. Harld T. Schupp, Markus Junghöfer, Almut I. Weike, and Alfons O. Hamm, "The selective processing of briefly presented affective pictures: An erp analysis," *Psychophysiology*, vol. 41, pp. 441–449, 2004.

10 M.K. Petersen, C. Stahlhut, A. Stopczynski, J.E. Larsen and L.K. Hansen

7. G.N. Ranky and S. Adamovich, "Analysis of a commercial eeg device for the control of a robot arm," in *IEEE 36th Annual Northeast Bioengineering Conference*, 2010, vol. IEEE Explore DOI: 10.1109/NEBC.2010.5458188.
8. Chuck Squatriglia, "Thinking your way through traffic in a brain-controlled car," *Wired*, vol. <http://www.wired.com/autopia/2011/03/braindriver-thought-control-car/>, 2011.
9. Andrew T. Campbell, Tanzeem Choudhury, Shaohan Hu, Hong Lu, Matthew K. Mukerjee, Mashfiqui Rabbi, and Rajeev D.S. Raizada, "Neurophone: brain-mobile phone interface using a wireless eeg headset," in *ACM MobiHeld*, 2010, pp. 1–6.
10. Scott Makeig, Klaus Gramann, Tzyy-Ping Jung, Terrence J Sejnowski, and Howard Poizner, "Linking brain, mind and behavior," *Int J Psychophysiol*, vol. 73, no. 2, pp. 95–100, 2009.
11. Andrea de Cesarei and Maurizio Codispoti, "When does size not matter? effects of stimulus size on affective modulation," *Psychophysiology*, vol. 43, pp. 207–215, 2006.
12. Christos A. Frantzidis, Charalampos Bratsas, Christos L. Papadelis, Evdokimos Konstantinidis, Costas Pappas, and Panagiotis D. Bamidis, "Toward emotion aware computing: an integrated approach using multichannel neurophysiological recordings and affective visual stimuli," *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no. 3, pp. 589–597, 2010.
13. Pierre Comon, "Independent component analysis, a new concept?," *Signal processing*, vol. 36, pp. 287–314, 1994.
14. Arnaud Delorme and Scott Makeig, "Eeglab: an open source toolbox for analysis of single-trial eeg dynamics including independent component analysis," *Journal of Neuroscience Methods*, vol. 134, no. 1, pp. 9–21, 2004.
15. Arnaud Delorme, Tim Mullen, Christian Kothe, Zeynep Akalin Acar, Nima Bigdely-Shamlo, Andrey Vankov, and Scott Makeig, "Eeglab, sift, nft, bcilab and erica: new tools for advanced eeg processing," *Computational Intelligence and Neuroscience*, vol. doi:10.1155/2011/130714, pp. 1–12, 2011.
16. Ian T. Jolliffe, *Principal Component Analysis*, Springer Series in Statistics. Springer, 1986 (2002).
17. Michel Besserve, Jacques Martinerie, and Line Garnerio, "Improving quantification of functional networks with eeg inverse problem: Evidence from a decoding point of view," *NeuroImage*, vol. 55, no. 4, pp. 1536–1547, 2011.
18. S. Baillet, J.C. Mosher, and R.M. Leahy, "Electromagnetic brain mapping," *IEEE Signal Processing Magazine*, vol. 18, pp. 14–30, 2001.
19. M.S. Hämäläinen and R.J. Ilmoniemi, "Interpreting magnetic fields of the brain: minimum norm estimates," *Medical and biological engineering and computing*, vol. 37, no. 1, pp. 35–42, 1994.
20. Annekathrin Schacht and Werner Sommer, "Emotions in word and face processing - early and late cortical responses," *Brain and Cognition*, vol. 69, pp. 538–550, 2009.
21. Antonio Damasio, *Looking for Spinoza*, Vintage, 2003.
22. Jonathan Posner, James A. Russell, Andrew Gerber, Daniel Gormn, Tiziano Colibazzi, Shan Yu, Zhishunn Wang, Alayar Kangarlu, Hongtu Zhu, and Bradley S. Peterson, "The neurophysiological bases of emotion: an fmri study of the affective circumplex using emotion-denoting words," *Human Brain Mapping*, pp. 883–895, 2009.
23. Margaret M. Bradley and Peter J. Lang, "Affective norms for english words (anew): Stimuli, instruction manual and affective ratings," Tech. Rep., The Center for Research in Psychophysiology, University of Florida, 1999.

APPENDIX F

The Smartphone Brain Scanner: A Portable Real-time Neuroimaging System

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The Smartphone Brain Scanner: A Portable Real-Time Neuroimaging System

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Abstract

Combining low-cost wireless EEG sensors with smartphones offers novel opportunities for mobile brain imaging in an everyday context. Here we present the technical details and validation of a framework for building multi-platform, portable EEG applications with real-time 3D source reconstruction. The system – *Smartphone Brain Scanner* – combines an off-the-shelf neuroheadset or EEG cap with a smartphone or tablet, and as such represents the first fully portable system for real-time 3D EEG imaging. We discuss the benefits and challenges, including technical limitations as well as details of real-time reconstruction of 3D images of brain activity. We present examples of brain activity captured in a simple experiment involving imagined finger tapping, which shows that the acquired signal in a relevant brain region is similar to that obtained with standard EEG lab equipment. Although the quality of the signal in a mobile solution using an off-the-shelf consumer neuroheadset is lower than the signal obtained using high-density standard EEG equipment, we propose mobile application development may offset the disadvantages and provide completely new opportunities for neuroimaging in natural settings.

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Introduction

In the last few years, the research communities studying human behavior have gained access to unprecedented computational and sensing power that basically “fits into a pocket”. This has happened for both specialized equipment used for building research tools, such as Reality Mining Badges [1] or accelerometer sensors [2], and for consumer-grade, off-the-shelf devices. Smartphones and tablets are capable of sensing, processing, transmitting, and presenting information. This has already had a significant impact on many research domains, such as social science [3], computer-human interaction [4], and mobile sensing [5,6]. In neuroscience there is a widely recognized need for mobility, i.e., for devices that support quantitative measurements in natural settings [7–9]. Here we present our work on the *Smartphone Brain Scanner*, investigate the feasibility of off-the-shelf, consumer-grade equipment in a neuroscience context, and build a mobile real-time platform for stimulus delivery, data acquisition, and processing with a focus on *real-time imaging* of brain activity.

Consumer-grade neuroheadsets, capable of recording brain activity generated by post-synaptic potentials of firing neurons, captured through electrodes placed on the scalp using Electroencephalography (EEG), have only recently made mobile brain monitoring feasible. Seen from a mental state decoding perspective, even a single channel EEG recording measuring the changes in electrical potentials (based on a passive dry electrode positioned at the forehead and a reference typically placed on the earlobe), allows for measuring mental concentration and drowsiness by assessing the relative distribution of frequencies in brain-wave patterns throughout the day. Simply measuring the dynamic

variability of brain-wave frequency components in a mobile scenario may be translated into neural signatures, e.g., reflecting whether a user is on the phone while driving a car [10]. Similarly, positioning the single EEG electrode headband over the temple may provide the foundation for building a Brain-Computer Interface (BCI) utilizing the ability to capture steady-state visual-evoked potentials (SSVEP) from the visual cortex when looking at flashing lights patterns, and thereby design a BCI interface for prediction with high accuracy and no previous training when a disabled user is focusing on a specific area of a screen, based on the time-locked EEG traces automatically generated as multiples of the particular flashing light frequencies [11].

As an example of the underlying technology used in several consumer products, the ThinkGear module manufactured by NeuroSky (<http://www.neurosky.com/Products/ThinkGearAM.aspx>) integrates a single dry electrode (reference and ground) attached to a headband. Essentially a system on a chip, it provides A/D conversion and amplification of one EEG channel, capable of capturing brain-wave patterns in the 3–100 Hz frequency range, recorded at 512 Hz sampling rate. Consumer neuroheadsets, such as those manufactured by Emotiv (<http://www.emotiv.com>) provide low-density neuroimaging based on 16 electrodes and typically support real-time signal processing in order to complement standard EEG measures with aggregate signals, which provide additional information on changes in mental state, or facilitate control of peripheral devices related to games. Their portability and built-in wireless transmission makes them suitable for the development of fully mobile systems, allowing for running EEG experiments in natural settings. The improved comfort of

these mobile solutions also allows for extending neuroimaging experiments over several hours. Furthermore, the relatively low cost of the neuroheadsets and mobile devices potentially opens new opportunities for conducting novel types of social neuroscience experiments, where multiple subjects are monitored while they interact [12,13].

However, such 'low-fi' mobile systems present a number of challenges. In real-time applications requiring signal processing to be performed with the lowest possible delay in order to present feedback to the user, the limited computational power of mobile devices may be a constraint. A solution might be to offload parts of the processing to an external server and retrieve the processed results over the network. This approach, however, requires network connection, possibly with low and constant delays, as well as more complicated client-server architecture. Also in terms of battery life, the local computation is more power-efficient than continuous transmission to the server and back. Consumer-grade mobile devices also present technical challenges for writing high-quality software; the devices operate on systems that are not real-time (RTOS), as they do not guarantee certain delays in data processing, and as such are ill-suited for time-sensitive tasks. These limitations might also affect timing of visual or auditory stimuli presentation, as well as synchronization with other sensors. From a neuroscience perspective, low-resolution recordings and artifacts induced in a mobile setup both present significant challenges. Noise and confounds are introduced by movement of the subject and electrical discharges, while the positioning of the electrodes might be less than ideal when compared to a standard laboratory EEG setup [14–17]. Nevertheless, we hold that these drawbacks are clearly offset by the advantages of being able to conduct studies incorporating larger groups of subjects over extended periods of time in more natural settings. We suggest that mobile EEG systems can be considered from two viewpoints: as stand-alone portable low-fi neuroimaging solutions, or as an add-on for retrieving neuroimaging data under natural conditions complementary to standard neuroimaging lab environments.

In terms of software programming, creating a framework for applications in C++ rather than in prevalent environments such as MATLAB, while approaching the problem as a smartphone sensing challenge, might enable new types of contributions to neuroscience. The Human-Computer Interaction (HCI) community is already starting to apply consumer-grade headsets to extend existing paradigms [18], thus incorporating neuroscience as a means to enhance data processing. Similarly, the availability of low-cost equipment means even general 'hacker-and-tinkers' audiences will almost certainly gain interest in using neuroscience tools (<http://neurogadget.com>). We see a great value in the emerging potential of entirely new groups of researchers and developers becoming interested in neuroscience and obtaining tools allowing them to develop new kinds of applications.

In a previous communication [19], we discussed opportunities and challenges in mobile and portable EEG. Here we address the foundations of the Smartphone Brain Scanner system, focusing on engineering and technical aspects of both software and hardware components. We describe the computational architecture of the framework, and discuss timing, reliability, and quality of the obtained signal. In particular we report on the results of a validation experiment comparing the system with a conventional EEG acquisition system in a prototypical application.

Related Work

Our real-time imaging EEG setup mediates between two hitherto disparate fields in sensorics, being on the one hand a down-sized neuroimaging device and on the other hand a

sophisticated smartphone sensor system for cognitive monitoring in natural conditions. We therefore briefly review the state of the art in both domains.

Neuroimaging. Several software packages for offline and online analysis of biomedical and EEG signals are available. The most popular packages for off-line analysis are EEGLAB and FieldTrip; for building real-time BCI-oriented applications, notable frameworks are BCILAB, OpenViBE, and BCI2000.

EEGLAB is a toolbox for the MATLAB environment and is useful for processing collections of single-trial or averaged EEG data [20]. Functions available in this framework include data importing, preprocessing (artifact rejection, filtering), independent component analysis (ICA), and others. The framework can be used via a graphical interface or by directly manipulating MATLAB functions. The toolbox is available as an open source (GNU license) and can be extended to incorporate various EEG data formats coming from different hardware. Similarly, FieldTrip is an open source (GNU License) MATLAB toolbox for the analysis of MEG, EEG, and other electrophysiological data [21]. Among others, FieldTrip has pioneered high-quality source reconstruction methods for EEG imaging. FieldTrip has support for real-time processing of data based on a buffer construction that allows chunking of data for further processing in the MATLAB environment.

BCILAB is a toolbox for building online Brain-Computer Interface (BCI) models from available data [22]. It is a plugin for EEGLAB running in MATLAB, providing functionalities for designing, learning, use, and evaluation of real-time predictive models. BCILAB is focused on operating in real-time for detecting and classifying cognitive states. The classifier output from BCILAB can be streamed to a real-time application to effect stimulus or prosthetic control, or may be derived post-hoc from recorded data. The framework is extensible in various layers; additional EEG hardware as well as data processing steps (e.g., filters and classifiers) can be added. But as these toolboxes are developed within the MATLAB environment, neither FieldTrip's real-time buffer nor BCILAB are suitable for mobile application development.

OpenViBE is a software framework for designing, testing, and using Brain-Computer Interfaces [23]. The main application fields of OpenViBE are medical i.e., assistive technologies, bio- and neurofeedback as well as virtual reality multimedia applications. OpenViBE is an open source (LGPL 2.1) and targets an audience focused on building real-time applications for Windows and Linux Operating Systems, and does not specifically support light-weight mobile platforms. A similar C++ based framework for building real-time BCI applications is BCI2000 [24]. A comprehensive review of the BCI frameworks can be found in [25]. Some of the consumer EEG systems also include Software Development Kits (SDKs), allowing for data acquisition, processing, and building applications. Emotiv SDK, available with the Research Edition of the Emotiv system is multi-platform, currently running on Linux, OSX, and Windows. The SDK allows for building applications, either using raw EEG data or extracted features, including affective state and recognition of facial expressions based on eye movements. The extracted features can be integrated into a C++ or C# application through a set of dynamically linked libraries. Although such SDK frameworks can greatly speed up the process of building BCI applications, they are mostly targeted towards scenarios where immediate feedback is available, such as gaming, and it remains a challenge to validate or tweak code for custom needs. To sum up, none of the aforementioned software platforms can easily be adapted to support mobile and embedded devices.

There exist various repositories of openly available human EEG data [26,27]. Such datasets contain both recordings from high-density and low-density systems and are an important tool for advancing the field. We feel that the increased availability of EEG systems will result in even more publicly available data. Although very beneficial for the field, this will undoubtedly raise concerns about the privacy of the subjects, whose very sensitive data in the form of EEG recordings, will possibly exist indefinitely.

Cognitive monitoring systems. Mobile brain imaging might also be viewed as yet another sensor extension to self-tracking applications, which have become prevalent with smartphones and the emergence of low-cost wearable devices - lowering the barriers for people to engage in life logging activities [28]. With the availability of multiple embedded sensors, modern smartphones have become a platform for out-of-the-box data acquisition of mobility (GPS, cellular network, WiFi), activity level (accelerometer), social interaction (Bluetooth, call, and text logs), and environmental context (microphone, camera, light sensor) [3]. Recently, non-invasive recording of brain activity has become common as several low-cost commercial EEG neuro-headset and headband systems have been made available, including the previously mentioned Emotiv EPOC and NeuroSky, the InteraXon Muse (<http://www.interaxon.ca/>), Axio (<http://www.axioinc.com/>), and Zeo (<http://myzeo.com/>). These sensors support applications ranging from BCI, game control, stress reduction, and cognitive training, to sleep monitoring. These neuroheadsets feature up to 16 electrodes, but ongoing developments promise next-generation low-cost EEG devices with a significantly higher number of electrodes, better quality signals, and improved comfort. The Smartphone Brain Scanner framework described in this paper can be used with mobile EEG devices with various numbers of electrodes to allow for capture of neuroimaging data over several hours. Battery tests on Samsung Galaxy Note with all wireless radios and screen turned off resulted in 11 hours of uninterrupted recording and storage of data from an Emotiv EPOC headset. However, current generation neuroheadsets are limited by their solution-based electrodes, which dry out. More comfortable designs [29,30] may be required for continuous mobile neuroimaging throughout the day.

Beyond EEG, multiple bio signals and physiological parameters can contribute to cognitive state monitoring, such as respiratory rate [31], heart rate variability, galvanic skin response [32], blood pressure, oxygen saturation, body/skin temperature, ECG, EMG, and body movements [33]. A webcam or a camera embedded in a smartphone can allow measurements of heart rate, variability, and respiratory rate by analyzing the color channels in the video signal [34]. Continuous monitoring of heart rate is enabled by pulse watches (<http://www.polar.com/>) and recently by the Basis Band wrist-worn sensor (<http://www.mybasis.com/>), which allows 24/7 recording under a subset of conditions (non-workout situations). Both continuous heart rate monitoring solutions allow user mobility and measurements in natural conditions. The Q Sensor from Affectiva (<http://www.affectiva.com/>) is an example of a system for monitoring galvanic skin response (GSR) and accelerometer and temperature data from a wrist-worn device. FitBit (<http://www.fitbit.com/>) is an example of a wearable pedometer, monitoring number of steps taken, distance traveled, calories burned, and floors climbed.

Methods: Smartphone Brain Scanner

The *Smartphone Brain Scanner* (SBS2) is a software platform for building research-oriented and end-user-oriented multi-platform EEG applications. The focus of the framework is on mobile devices (smartphones, tablets) and on consumer-grade (low-density

and low-cost) mobile neurosystems (see Figure 1). The SBS2 is freely available under the MIT License on GitHub at <https://github.com/SmartphoneBrainScanner>. The repositories contain the core of the framework, as well as example applications. The documentation hosted on GitHub wiki pages (<https://github.com/SmartphoneBrainScanner/smartphonebrainscanner2-core/wiki>) includes instructions for compiling the software, building the hardware components, preparing the devices, and writing custom applications. An active mailing list for developers also exists at <https://groups.google.com/forum/#forum/smartphonebrainscanner2-dev>.

The SBS2 framework is divided into three layers: low-level data acquisition, data processing, and applications. The first two layers constitute the core of the system and include common elements used by various applications. An overview of the architecture is shown in Figure 2.

Smartphone Brain Scanner

Key features. With a focus on the mobile devices, SBS2 is a multi-platform framework. The underlying technology - Qt - is an extension of C++ and is currently supported on the main desktop operating systems (Linux, OSX, Windows) as well as on mobile devices (Android, BB10, and partially iOS, see <http://qt.digia.com/Product/Supported-Platforms/>).

We have aimed for a modular framework, allowing for adding and modifying data acquisition and processing blocks. The modules are created as C++ classes and integrate directly with the core of the framework. The framework supports building real-time applications; data can be recorded for subsequent off-line analysis. However, most of the implemented data-processing blocks aim to provide real-time functionality for working with the EEG signal. The applications developed with SBS2 can be installed on both desktop and mobile devices; installation can be started by the user and distributed via regular channels, such as repositories and application stores.

Data acquisition. The Data Acquisition layer is responsible for setting up communication with an EEG device, acquiring the raw data, and forming packets. Three primary objects are used: Sbs2Mounter, Sbs2DataReader, and Sbs2Packet, thereby abstracting all the specificities of the EEG systems (hardware) and of the OS+ device running the software (platform). Different embedded devices, even with the same OS, may require a specific code for certain low-level functionalities, for example to access the USB port. A higher-fidelity architecture is shown in Figure 3. The EEG hardware is set up by a specialized Sbs2Mounter object. The information about the hardware (e.g. mounting point, serial number) is passed to a Sbs2DataReader object. This object subsequently begins reading the raw data from the hardware. The raw data are passed to a Sbs2Packet object to create a proper encapsulation, setting the values for all the EEG channels and metadata. Once formed, the packet is pushed to the Data Processing layer via a Sbs2Callback object.

The Data Acquisition layer of the SBS2 was originally designed to support the Emotiv EEG headset. It has been extended to support additional hardware, such as custom made EasyCap hardware, by implementing additional classes of the hardware mounter, data reader, and packet creator. For Emotiv headset, this layer also contains the data decryption module, as the stream coming from the device is encrypted.

Mounting the EEG hardware on a desktop and embedded devices requires drivers, either standard kernel modules or proprietary drivers created by the vendor. The Emotiv EPOC USB receiver is mounted as `/dev/hidraw` in Linux (desktop and Android), provided the device and the kernel support the USB host mode and have the HIDRAW module enabled. Most desktop

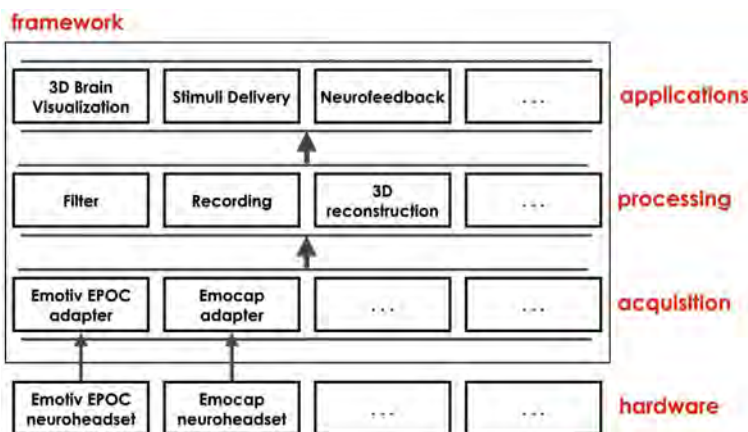


Figure 1. Smartphone Brain Scanner applications running on Android devices. Neurofeedback training and real-time 3D source reconstruction running on Android mobile devices via a wireless connection to an Emotiv or EasyCap EEG systems.
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Linux flavors have both by default, but currently most Android mobile devices only support the USB host mode out-of-the-box. In the current implementation, a custom kernel needs to be compiled with the HIDRAW module enabled. Reading the data directly from the `/dev/hidraw` device requires 'root' privileges, which must be enabled on Android devices to acquire data from the Emotiv EPOC receiver. This is possible for most recent Android devices, e.g. for the Nexus (developer) line of devices. We can expect that the next generation of mobile neuroheadsets will use standardized Bluetooth low-energy protocols and Android devices will be able

to support them by default. This will likely have a significant impact on the adoption of neuroimaging outside lab environments.

Data processing. Well-formed EEG packet objects are used for data processing. The functionality of this layer is hardware-agnostic and depends only on packet content, i.e. data for the EEG channels, reflecting a particular sensor configuration, and sampling frequency. Single packets are dispatched to different processing objects and methods, including recording, filtering, 3D reconstruction, etc. Some operations need to collect data into frames and run asynchronously (in separate thread), pushing the results back to the callback object once the results are ready.

Sbs2Callback is an object implementing the `getData(Sbs2Packet*)` method, to which single packets are always passed and can then be dispatched to the `Sbs2DataHandler` or pushed to the Application layer. `Sbs2DataHandler` is an object providing methods for data processing, by delegating them to specialized objects, including `Sbs2FileHandler` and `Sbs2Filter`.

The framework for data processing is extensible and new modules can be added to the core; the data handler prepares the data in a format expected by the processing block (e.g. collecting packets into larger frames) and runs the processing method. The currently implemented blocks allow for a variety of processing operations. The raw EEG data can be recorded, including time-stamped events (stimuli onsets, user responses, etc.). Raw packets, as well as extracted features and arbitrary values, can be streamed over the network for either data processing or interconnection between devices (multiplayer gaming is one example). Other methods for data processing, including filter, FFT, spatial filter (CSP), and classifier (LDA), are also implemented and can be used for building the pipelines.

3D Imaging

The most advanced data-processing block of the Smartphone Brain Scanner is the source reconstruction aimed at real-time 3D imaging as demonstrated in Figure 4. Videos demonstrating the Smartphone Brain Scanner are available at <http://milab.imm.dtu.dk/ceg>. Source reconstruction estimates the current sources within the brain most likely to have generated the observed EEG signal at



Figure 2. Overview of the layered architecture of the SBS2 framework. Data from the connected EEG hardware are acquired and extracted by specific adapters and all subsequent processing is hardware agnostic. The empty boxes indicate the extensibility of the architecture allowing additional hardware devices for data acquisition and additional processing methods.
doi:10.1371/journal.pone.0086733.g002

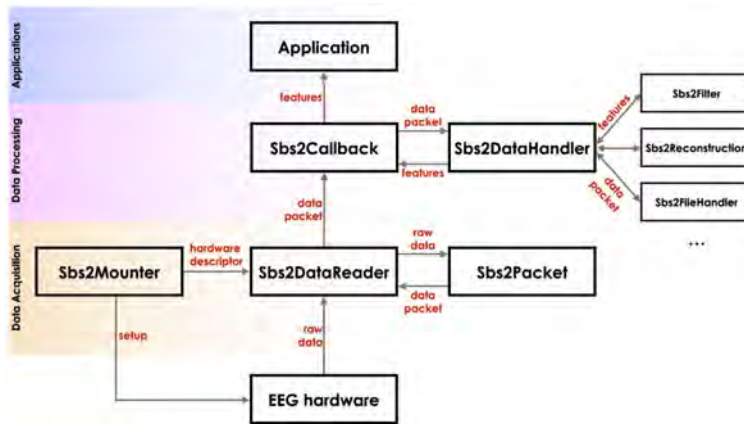


Figure 3. The Smartphone Brain Scanner architecture. Data are acquired in the first layer from the EEG hardware, passed to the Data Processing Layer, and extracted. Features, as well as raw values, are then available for applications.
doi:10.1371/journal.pone.0086733.g003

scalp level. As the number of possible source locations far exceeds the number of channels, this is known to be an extremely ill-posed inverse problem. A unique solution is obtained by imposing prior information in correspondence with anatomical, physiological, or mathematical properties [35–37]. Implemented inverse methods in the SBS2 cover Bayesian formulations of the widely used Minimum-norm method (MN) [37] and low-resolution electromagnetic tomography (LORETA) [38]. The Bayesian formulation used in the SBS2 framework allows adaptation of hyper-parameters to different noise environments in real-time. This is an improvement over previous real-time source reconstruction approaches [39–41] that applied heuristics to estimate the parameters involved in the inverse method. The current source reconstruction is based on an assumed forward model matrix, \mathbf{A} , connecting scalp sensor signals \mathbf{Y} (channel by time) and current sources \mathbf{S} (cortical locations by time) [42]

$$\mathbf{Y} = \mathbf{A}\mathbf{S} + \mathcal{E}. \quad (1)$$

The term \mathcal{E} accounts for noise not modeled by the linear generative model. When estimating the forward model a number of issues are taken into consideration, such as sensor positions, the geometry of the head model (spherical or ‘realistic’ geometry), and tissue conductivity values [43–45]. With the forward model \mathbf{A} given and the linear relation in Eq. (1), the source generators can be estimated. We assume the noise term to be normally distributed, uncorrelated, and time-independent, which leads to the probabilistic formulation:

$$p(\mathbf{Y}|\mathbf{S}) = \prod_{t=1}^{N_t} \mathcal{N}(\mathbf{y}_t | \mathbf{A}\mathbf{s}_t, \beta^{-1}\mathbf{I}_{N_c}) \quad (2)$$

$$p(\mathbf{S}) = \prod_{t=1}^{N_t} \mathcal{N}(\mathbf{s}_t | 0, \alpha^{-1}\mathbf{L}^T\mathbf{L}). \quad (3)$$

Where $p(\mathbf{S})$ is the prior distribution over \mathbf{S} with \mathbf{L} given as a graph

Laplacian ensuring spatial coherence between sources and β^{-1} as the noise variance. Using Bayes’ rule, the posterior distribution over the sources is maximized by

$$p(\mathbf{S}|\mathbf{Y}) = \prod_{t=1}^{N_t} \mathcal{N}(\mathbf{s}_t | \boldsymbol{\mu}_t, \boldsymbol{\Sigma}_t)$$

$$\boldsymbol{\Sigma}_t = \alpha^{-1}\mathbf{I}_{N_d} - \alpha^{-1}\mathbf{A}^T\boldsymbol{\Sigma}_y\mathbf{A}\alpha^{-1}$$

$$\boldsymbol{\Sigma}_y^{-1} = \alpha^{-1}\mathbf{A}\mathbf{L}^T\mathbf{L}\mathbf{A}^T + \beta^{-1}\mathbf{I}_{N_c} \quad (4)$$

$$\hat{\mathbf{s}}_t = \alpha^{-1}\mathbf{A}^T\boldsymbol{\Sigma}_y\mathbf{y}_t. \quad (5)$$

Here, \mathbf{L} denotes a spatial coherence matrix, which in the current form takes advantage of the graph Laplacian using a fixed smoothness parameter (0.2).

Handling noise estimation is a crucial part for acquiring reliable source estimates. We have previously examined how eye-related artifacts can corrupt the source estimates for low density EEG caps with unevenly distributed sensors such as the Emotiv EPOC [19]. While we here have adopted the assumption of the noise to be uncorrelated, correlated noise can easily be included in the model above, either directly in the model or indirectly through pre-processing the data prior to the source modeling. Direct modeling of the correlated noise can be achieved by replacing the identity matrix \mathbf{I}_{N_c} with a full noise covariance matrix $\boldsymbol{\Sigma}_{\mathcal{E}}$. Estimation of the noise covariance matrix could e.g. be carried out through calibration sessions. By online estimating the hyperparameter β the inverse solver continuously can model the amount of noise present in the data.

The present data analytic pipeline does not include real-time artifact reduction steps, hence cleaning of data for eye, muscle, or motion induced artifacts must be carried out post hoc in the



Figure 4. Snapshot of the SBS2 real time brain imaging system running on a Samsung Galaxy Note 2. EEG recorded using the Emocap [29], based on the Emotiv EEG wireless transmission setup. Visible in the picture is the entire setup required for data acquisition, processing, and visualization. The subject of the photograph has given written informed consent, as outlined in the PLOS consent form, to publish this photograph.
doi:10.1371/journal.pone.0086733.g004

present system. Thus real-time imaging experiments, bio-feedback etc. should be done under circumstances that reduce artifacts.

Methods: Experimental Designs

In this section we briefly describe the design of the experiments demonstrating and validating the potential of the SBS2 framework, the specific hardware, and the mobile approach in general.

Timing and Data Quality

First, we analyzed the data and timing quality. Many neuroscience paradigms rely heavily on accurate synchronization between EEG signal and stimuli, user response, or data from other sensors (e.g., P300, steady state visual evoked potentials). However, we can also envision applications in which the present 'low-cost' mobile setup will be used to collect data from many subjects over extended periods, where precise synchronization is less important.

Emotiv EEG sampling. The measurements are all based on the Emotiv EEG neuroheadset. The nominal sampling frequency of this neuroheadset is 128 Hz (down-sampled from internal 2048 Hz). For validation purposes we tested the actual sampling

rate obtained from three randomly picked Emotiv devices (10×10 min measurements for each).

Data quality. The Emotiv hardware adds a modulo 129 counter (0–128) to every packet transmitted from the device. This allows for data quality control (dropped packets) with the accuracy of a modulo 129. It is possible to obtain long recordings (over one hour) using this neuroheadset and SBS2. The battery in the Emotiv hardware is rated at 12h of continuous operation; in recording-only setup, a mobile device such as Galaxy Note (offline mode, screen off, only decrypting and recording) lasts for around 10h. Provided good visibility between the Emotiv EEG neuroheadset transmitter (located in the back part of the headset) and the USB receiver was maintained, we were able to achieve zero packet loss in the full rundown recording. In order to acquire an EEG signal of good quality, the impedance between the electrodes and the scalp should be kept under $5k\Omega$. The Emotiv headset embeds the channel-quality information in the signal directly (2 Hz per channel, multiplexed into the signal). The values are unscaled, and come from applying a square wave of 128Hz to the DRL feedback circuit and extracting the amplitude of the inherent square wave using phase-locked detection on each channel. In principle, the obtained values can be calibrated using a known impedance. For regular usage, however, the hardware manufacturer assures the green color of the indicator (channel quality value greater than 407) corresponds to sufficiently low impedance of the electrode. From our experience with the system this appears correct.

Timing. In order to measure the total delay in the system, we used the setup as depicted in Figure 5. A sinusoidal audio tone of 10Hz, with its trailing and following periods of silence, was generated and amplified so it could be detected by the EEG hardware and also so it could be split into oscilloscope and EEG hardware. The software on the device performed peak detection on the signal and visualized the peaks by changing the screen color from black to white. This change was detected by a photocell, connected to the second channel of the oscilloscope. We can then calculate $dt1 = t2 - t1$, indicating the total delay of the system from the physical signal reaching the EEG hardware to being visualized on the screen (without any additional processing), see Figure 6. We also look at the jitter $dt2$ as the difference between *min* and *max* values of $dt1$. The observed delta depends on the EEG sampling rate (here 128Hz), the processing power of the device, and the screen refresh rate (60Hz for all tested devices).

Imagined Finger Tapping

One of the most widely investigated paradigms in the BCI literature is a task in which a subject is instructed to select between two or more different imagined movements [19,46–49]. Such experiments are rooted in a central aim of many BCI systems,

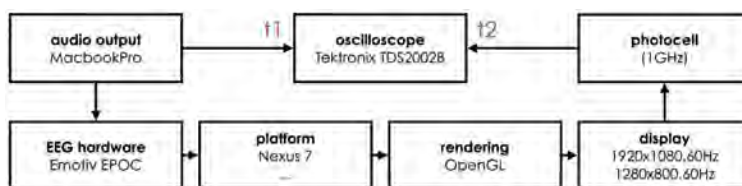


Figure 5. The timing measurement setup. 10 Hz sinusoid is generated with a computer sound card, amplified, and fed into an oscilloscope and the EEG hardware. The device acquiring the EEG data responds to the sinusoid signal with changes of screen brightness, which is detected by a photocell connected to the oscilloscope. The time difference between the two signals is used to calculate the system delay.
doi:10.1371/journal.pone.0086733.g005

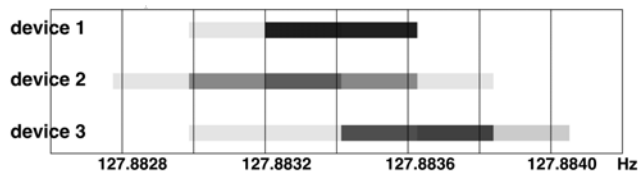


Figure 6. System response timings. The system responds to the sinusoid signal peak (time 0). The red color ($dt1$) indicates minimal observed delay; the blue color ($dt2$) indicates jitter. Galaxy Note running Android 4.0.1, 60 Hz AMOLED screen, $dt1 = 125ms$, $dt2 = 16ms$; Nexus 7 running Android 4.1.1, 60 Hz IPS LCD screen, $dt1 = 85ms$, $dt2 = 26ms$; MacBookPro, LCD screen (60 Hz), $dt1 = 80ms$, $dt2 = 26ms$. doi:10.1371/journal.pone.0086733.g006

namely of being able to assist patients with severe motor disabilities to communicate by 'thought'. In this contribution we replicated a classical experiment with imagined finger tapping (left vs. right) inspired by [49]. The setup consisted of a set of three different images with instructions: *Relax*, *Left*, *Right*. In order to minimize the effect of eye movements, the subject was instructed to focus on the center of the screen, where the instructions also appeared (3.5 inch display size, 800×480 pixels resolution, at a distance of 0.5 m). The instructions *Left* and *Right* appeared in random order. A total of 200 trials were conducted for a single subject.

Results and Discussion

In this section we present and discuss the results of the experiments, validating the performance of the software, the platforms used, and the EEG hardware. These results aim to validate the underlying framework with respect to key engineering aspects and to outline the potential and limitations of the system, especially from the user and developer perspective. More complex experiments conducted using the system are described in [19].

Timing and Data Quality

Emotiv EEG sampling. From Figure 7 we can see that the Emotiv EPOC hardware a) has an actual sampling rate close to 127.88 Hz and b) keeps this sampling rate in a fairly consistent manner. Depending on the analysis performed on the data, one

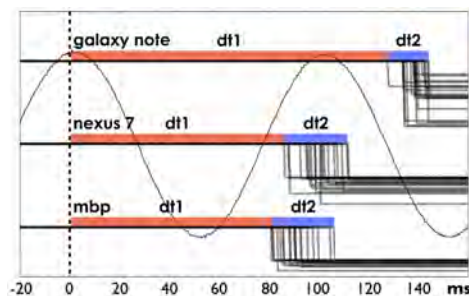


Figure 7. Measured sampling frequency, including measurement resolution for three random Emotiv EEG devices, $10 \times 10min$ recordings for each. All measured rates, including uncertainty, are between 127.8828 Hz and 127.8841 Hz, which corresponds to .99908 and .99909 of nominal 128 Hz. The measurements were performed with 1 ms resolution (2 ms accuracy) on 76800 EEG packets. All tests were performed at normal temperature on a single day. We can note consistent results within and across devices. doi:10.1371/journal.pone.0086733.g007

can assume 128 Hz, 127.88 Hz, or measure the actual sampling rate for every Emotiv EPOC hardware device individually.

Timing. The results of the timing measurements (20 per device) are depicted in Figure 6.

We can see in the results for all devices that there is a significant delay between the signal reaching the EEG hardware and being fully processed in the software (80–125 ms). This delay, although significant, is fairly stable (16–26 ms jitter) and thus can be corrected for.

In the second set of measurements, we test the stability of the timing of the packets as they appear in the system. To measure this, we collect the packets from the Emotiv EPOC device and change the screen color every 4 packets (limited by screen refresh rate, 60 Hz). This change is then measured by a photocell, fed into the oscilloscope and the distance between the 4-packet packages is calculated. Figure 8 shows these measurements.

In summary, the stability and quality of the acquired signal is excellent. Most of the variations, including imperfect sampling rate or timing jitters, are constant and can largely be accounted for in the data analysis, if necessary.

3D source reconstruction on-device performance. Source imaging was obtained using the Bayesian inverse solver for the linear model in Eq. (1). The forward matrix \mathbf{A} and cortical source mesh grid was based on a coarse resolution (5124 vertices) of the SPM8 template brain [50], further reduced to 1028 using Matlab's function `reducepatch`. We tested the performance of 3D reconstruction and hyper-parameters calculation on 1 s of raw EEG signal. The results on different platforms show the time needed for the actual reconstruction (fast) and update of hyper-parameters (slower): MacBookPro8,2 (Intel Core i7 Sandy Bridge 2.2 GHz): 2 ms/2 s, Nexus 7: 8 ms/1 s, Galaxy Note: 8 ms/11 s, Acer Iconia: 14 ms/13 s. These results show that it is in fact possible to run 3D reconstruction of an EEG signal on

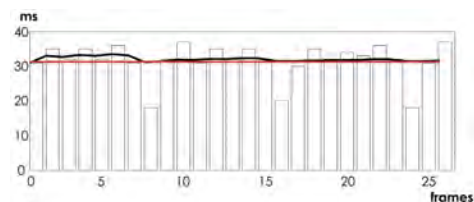


Figure 8. Distances between 4-sample frames. Red line indicates expected distance of $4/127.88 = 0.03106ms$ between the groups of four 127.88 packets. The bars indicate the observed distance. We can see that the Emotiv system compensates every $8 \times 4 = 32$ samples to keep the average (black line) at the correct level. doi:10.1371/journal.pone.0086733.g008

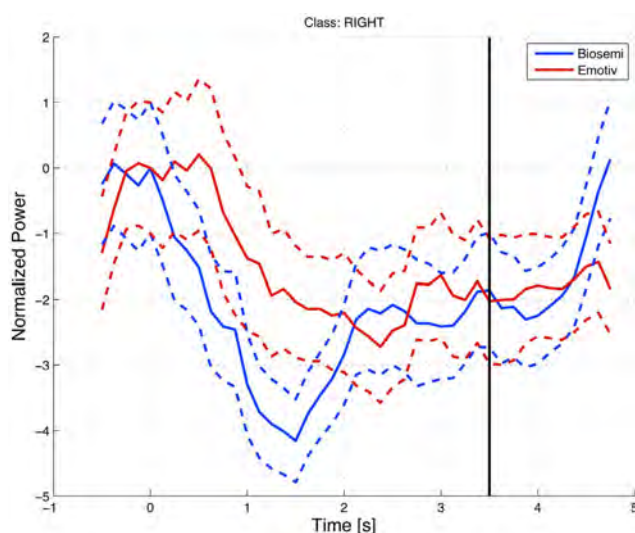


Figure 9. Finger-tapping results for Emotiv EEG and Biosemi standard equipment resampled to 14 channels. Mean (solid lines) and standard deviation (dashed lines) of reconstructed current source power in the left (L) Precentral AAL regions calculated across right-cued, imagined finger-tapping conditions. Mean activity was normalized to unit at $t = 0$. Both activities are based on 3D reconstruction with online estimation of the α and β parameters using the Minimum Norm approach.
doi:10.1371/journal.pone.0086733.g009

mobile devices several times a second, and to update the hyper-parameters several times a minute.

Imagined Finger Tapping – Online Source Reconstruction

In order to demonstrate the applicability of discriminating a simple task such as the left and right imagined finger tapping on the cortical source level in an online framework, the EEG data were acquired with the Emotiv EPOC neuroheadset and compared with EEG recordings acquired with a standard laboratory setting, viz. using 64 channels on a Biosemi Active-II device. The 64-channels were sub-sampled to represent the same channel locations as the Emotiv device.

Imagined finger tapping is known to lead to a suppression of alpha (8–13 Hz) activity over the premotor/motor regions, with the contralateral areas normally being more desynchronized [51]. Thus, imagined right-finger tapping should lead to alpha activity being suppressed in the left pre-motor region. In Figure 9, we show the responses obtained with SBS2 and the standard equipment, demonstrating the framework's ability to reconstruct online meaningful current sources within the given region. In particular, Figure 9 shows how alpha power (8–13 Hz) is suppressed over time in the region of interest - Precentral Left AAL (Automated Anatomical Labeling). Both responses are calculated as the averaged response over 87 and 79 responses to 'right imaging' cued trials that remained after rejecting trials with artifacts. Note that, while the result is presented as an average over runs, the source localization was carried out in online mode with model parameters (α and β) and current sources (S) estimated online. We note the similarity of the suppression of the alpha power in the Left Precentral AAL region to imagined right-finger tapping trials as obtained by the Emotiv EPOC and the Biosemi system. The possible implications of using portable and low-cost systems such

as *Smartphone Brain Scanner* in BCI context, together with more in-depth analysis of the finger tapping data are described in [19].

Conclusions

We have presented the design, implementation, and evaluation of the first fully portable 3D EEG imaging system: The *Smartphone Brain Scanner*. The open source software allows real-time EEG data acquisition and source imaging on standard off-the-shelf Android mobile smartphones and tablets with a good spatial resolution and frame rates in excess of 40 fps. In particular, we have implemented a real-time solver for the ill-posed inverse problem with online Bayesian optimization of hyper-parameters (noise level and regularization).

The evaluation showed that the combined system provides for a stable imaging pipeline with a delay of 80–120 ms. We showed results of a cued, imagined finger-tapping experiment and compared the smartphone brain scanner's average power in the alpha band in a relevant motor area with that of conventional state-of-the-art laboratory equipment and found that these aggregate signals compare favorably with those obtained with standard equipment. Both show the expected de-synchronization on initiation of imagined motor actions.

The work presented here is extended in [19], where we discuss the perspectives and challenges of mobile and portable EEG systems. That work also includes results from more complex experiments, including neurofeedback applications and measuring emotional responses.

Future developments in hardware and software will allow for even better signal acquisition and analysis from low-density and mobile setups. This includes electrodes of different type and form (e.g. dry) and positioned in a non-standard way (e.g. inside ear

canal). From the software perspective, more computation power available in the devices will allow for more powerful data processing and de-noising algorithms to be run (e.g. PCA-based or ICA-based artifacts rejection, more advanced 3D reconstruction), possibly using other available data sources (e.g. head movements obtained from gyroscopes). The present data analytic pipeline does not include real-time artifact reduction steps, hence cleaning of data for eye-, muscle-, or motion-induced artifacts must be carried out post hoc in the present system. Thus real-time imaging experiments, bio-feedback etc. should be done under circumstances that reduce artifacts.

We suggest the mobility and simplified application development may enable completely new research directions for imaging neuroscience and thus offset the expected reduced signal quality of

a mobile off-the-shelf, low-density neuroheadset relative to more conventional and controlled, high-density laboratory equipment.

Acknowledgments

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Author Contributions

Conceived and designed the experiments: AS CS MKP JEL LKH. Performed the experiments: AS CS MKP. Analyzed the data: AS CS LKH. Contributed reagents/materials/analysis tools: AS CS LKH. Wrote the paper: AS CS MKP JEL LKH.

References

- Choudhury T, Pentland A (2003) Sensing and modeling human networks using the sociometer. In: Proc. the 7th IEEE International Symposium on Wearable Computers (ISWC2003), pp. 216–222.
- Van Laerhoven K, Caknaki O (2000) What shall we teach our pants? In: Wearable Computers, The Fourth International Symposium on. IEEE, pp. 77–83.
- Aharony N, Pan W, Ip C, Khayal I, Pentland A (2011) Social fmri: Investigating and shaping social mechanisms in the real world. *Pervasive and Mobile Computing* 7: 643–659.
- Brown B, Reeves S, Sherwood S (2011) Into the wild: challenges and opportunities for field trial methods. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM, pp. 1657–1666.
- Jensen B, Larsen JE, Jensen K, Larsen J, Hansen LK (2010) Estimating human predictability from mobile sensor data. In: Machine Learning for Signal Processing (MLSP), 2010 IEEE International Workshop on. IEEE, pp. 196–201.
- Kwok R (2009) Personal technology: Phoning in data. *Nature* 458: 959.
- Makeig S, Gramann K, Jung T, Sejnowski T, Poizner H (2009) Linking brain, mind and behavior. *International Journal of Psychophysiology* 73: 95–100.
- Blankertz B, Tangermann M, Vidaurre C, Fazli S, Sannelli C, et al. (2010) The berlin brain-computer interface: non-medical uses of bci technology. *Frontiers in Neuroscience* 4.
- Gramann K, Gwin J, Ferris D, Oie K, Jung T, et al. (2011) Cognition in action: imaging brain/body dynamics in mobile humans. *Reviews in the Neurosciences* 22: 593–608.
- Yasui Y (2009) A brainwave signal measurement and data processing technique for daily life applications. *Journal of Physiological Anthropology* 28: 145–150.
- Luo A, Sullivan T (2010) A user-friendly sseep-based brain-computer interface using a time-domain classifier. *Journal of Neural Engineering* 7: 026010.
- Konvalinka I, Roepstorff A (2012) The two-brain approach: how can mutually interacting brains teach us something about social interaction? *Frontiers in Human Neuroscience* 6.
- Dumas G (2011) Towards a two-body neuroscience. *Communicative & Integrative Biology* 4: 349–352.
- Stahlhut C, Attias H, Stopczynski A, Petersen M, Larsen JE, et al. (2012) An evaluation of EEG scanner's dependence on the imaging technique, forward model computation method, and array dimensionality. In: 34th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 1–4.
- Chi Y, Wang YT, Wang Y, Maier C, Jung TP, et al. (2012) Dry and noncontact eeg sensors for mobile brain-computer interfaces. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 20: 228–235.
- Gramann K, Gwin JT, Bigdely-Shamlo N, Ferris DP, Makeig S (2010) Visual evoked responses during standing and walking. *Frontiers in Human Neuroscience* doi: 10.3389/fnhum.2010.00202.
- Gwin JT, Gramann K, Makeig S, Ferris DP (2010) Removal of movement artifact from high-density eeg recorded during walking and running. *Journal of Neurophysiology* doi: 10.1152/jn.00105.2010.
- Vi C, Subramanian S (2012) Detecting error-related negativity for interaction design. In: Proceedings of the 2012 ACM annual conference on Human Factors in Computing Systems. ACM, pp. 493–502.
- Stopczynski A, Stahlhut C, Petersen MK, Larsen JE, Jensen CF, et al. (2013) Smartphones as pocketable labs: Visions for mobile brain imaging and neurofeedback. *International Journal of Psychophysiology*. Available: <http://dx.doi.org/10.1016/j.jpsycho.2013.08.007>.
- Delorme A, Makeig S (2004) Eeglab: an open source toolbox for analysis of single-trial eeg dynamics including independent component analysis. *Journal of Neuroscience Methods* 134: 9–21.
- Oostenveld R, Fries P, Maris E, Schoffelen J (2011) Fieldtrip: open source software for advanced analysis of meg, eeg, and invasive electrophysiological data. *Computational Intelligence and Neuroscience* 2011: 1.
- Delorme A, Mullen T, Kothe C, Acar Z, Bigdely-Shamlo N, et al. (2011) Eeglab, sfti, nft, bcilab, and erica: new tools for advanced eeg processing. *Computational Intelligence and Neuroscience* 2011: 10.
- Renard Y, Lotte F, Gibert G, Congedo M, Maby E, et al. (2010) Openvibe: an open-source software platform to design, test, and use brain-computer interfaces in real and virtual environments. *Presence: Teleoperators and Virtual Environments* 19: 35–53.
- Schalk G, McFarland D, Hinterberger T, Birbaumer N, Wolpaw J (2004) Bci2000: a generalpurpose brain-computer interface (bci) system. *IEEE Transactions on Biomedical Engineering* 51: 1034–1043.
- Brunner C, Andreoni G, Bianchi L, Blankertz B, Breivieser C, et al. (2011) Bci software platforms. *Towards Practical Brain-Computer Interfaces* : 303–331.
- Dtu compute neuro wiki. Available: <http://neuro.compute.dtu.dk/wiki/Electroencephalography#Data>. Accessed 2013 Feb 27.
- Ucsd publicly available eeg data. Available: [http://scn.ucsd.edu/arno/fam2data/publicly available EEG data.html](http://scn.ucsd.edu/arno/fam2data/publicly%20available%20eeg%20data.html). Accessed 2013 Feb 27.
- Swan M (2012) Sensor mania! the internet of things, wearable computing, objective metrics, and the quantified self 2.0. *Journal of Sensor and Actuator Networks* 1: 217–253.
- Debener S, Minow F, Emkes R, Gandras K, Vos M (2012) How about taking a low-cost, small, and wireless eeg for a walk? *International Journal of Psychophysiology* 49: 1617–1621.
- Looney D, Kidmose P, Park C, Ungstrup M, Rank ML, et al. (2012) The in-the-car recording concept: User-centered and wearable brain monitoring. *Pulse, IEEE* 3: 32–42.
- Moraveji N, Adishesan A, Hagiwara T (2012) Breathtray: augmenting respiration self-regulation without cognitive deficit. In: CHI '12 Extended Abstracts on Human Factors in Computing Systems. New York, NY, USA: ACM, CHI EA '12, pp. 2405–2410. doi:10.1145/2212776.2223810. Available: <http://doi.acm.org/10.1145/2212776.2223810>.
- Poh M, Swenson N, Picard R (2010) A wearable sensor for unobtrusive, long-term assessment of electrodermal activity. *IEEE Transactions on Biomedical Engineering* 57: 1243–1252.
- Pantelopoulos A, Bourbakis N (2010) A survey on wearable sensor-based systems for health monitoring and prognosis. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews* 40: 1–12.
- Poh M, McDuff D, Picard R (2011) Advancements in noncontact, multiparameter physiological measurements using a webcam. *IEEE Transactions on Biomedical Engineering* 58: 7–11.
- Baillet S, Garnero L (1997) A bayesian approach to introducing anatomofunctional priors in the EEG/MEG inverse problem. *IEEE Transactions on Biomedical Engineering* 44: 374–385.
- Phillips C, Rugg M, Friston K (2002) Anatomically Informed Basis Functions for EEG Source Localisation: Combining Functional and Anatomical Constraints. *NeuroImage* 16: 678–695.
- Hamalainen M, Ilmoniemi R (1994) Interpreting magnetic fields of the brain: minimum norm estimates. *Medical & Biological Engineering & Computing* 32: 35–42.
- Pascual-Marqui RD, Michel CM, Lehmann D (1994) Low resolution electromagnetic tomography: a new method for localizing electrical activity in the brain. *International Journal of Psychophysiology* 18: 49–65.
- Congedo M, Lotte F, Lécuyer A (2006) Classification of movement intention by spatially filtered electromagnetic inverse solutions. *Physics in Medicine and Biology* 51: 1971–1989.
- Noirhomme Q, Kitey R, Macq B (2008) Single-trial eeg source reconstruction for brain-computer interface. *IEEE Transactions on Biomedical Engineering* 55: 1592–1601.
- Besserve M, Martinerie J, Garnero L (2011) Improving quantification of functional networks with eeg inverse problem: Evidence from a decoding point of view. *NeuroImage* 55: 1536–1547.
- Baillet S, Mosher J, Leahy R (2001) Electromagnetic brain mapping. *IEEE Signal Processing Magazine* 18: 14–30.

43. Wolters C, Kostler H, Moller C, Hardtlein J, Grasedyck L, et al. (2007) Numerical mathematics of the subtraction method for the modeling of a current dipole in EEG source reconstruction using finite element head models. *SIAM J Sci Comp* 30: 24–45.
44. Hallez H, Vanrumste B, Grech R, Muscat J, De Clercq W, et al. (2007) Review on solving the forward problem in EEG source analysis. *Journal of Neuroengineering and Rehabilitation* 4: 46.
45. Drechsler F, Wolters C, Dierkes T, Si H, Grasedyck L (2009) A full subtraction approach for finite element method based source analysis using constrained Delaunay tetrahedralisation. *NeuroImage* 46: 1055–1065.
46. Müller-Gerking J, Pfurtscheller G, Flyvbjerg H (1999) Designing optimal spatial filters for singletrial EEG classification in a movement task. *Clinical Neurophysiology* 110: 787–798.
47. Babiloni F, Cincotti F, Lazzarini L, Millan J, Mourino J, et al. (2000) Linear classification of low-resolution eeg patterns produced by imagined hand movements. *IEEE Transactions on Rehabilitation Engineering* 8: 186–188.
48. Dornhege G, Blankertz B, Curio G, Müller K (2004) Boosting bit rates in non-invasive EEG single-trial classifications by feature combination and multi-class paradigms. *IEEE Transactions on Biomedical Engineering* 51(6): 993–1002.
49. Blankertz B, Dornhege G, Krauledat M, Müller K, Kunzmann V, et al. (2006) The berlin braincomputer interface: Eeg-based communication without subject training. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14: 147–152.
50. Litvak V, Mattout J, Kiebel S, Phillips C, Henson R, et al. (2011) Eeg and meg data analysis in spm8. *Computational Intelligence and Neuroscience* 2011.
51. Pfurtscheller G, Lopes da Silva F (1999) Event-related eeg/meg synchronization and desynchronization: basic principles. *Clinical Neurophysiology* 110: 1842–1857.

APPENDIX G

An Evaluation of EEG Scanner's Dependence on the Imaging Technique, Forward Model Computation Method, and Array Dimensionality

Carsten Stahlhut, Hagai Thomas Attias, **Arkadiusz Stopczynski**, Michael Kai Petersen, Jakob Eg Larsen, and Lars Kai Hansen. An evaluation of EEG scanner's dependence on the imaging technique, forward model computation method, and array dimensionality. *Engineering in Medicine and Biology Society (EMBC)*, 2012 Annual International Conference of the IEEE, pp. 1538-1541. IEEE, 2012.

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An Evaluation of EEG Scanner's Dependence on the Imaging Technique, Forward Model Computation Method, and Array Dimensionality

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Michael Kai Petersen¹ Jakob Eg Larsen¹, Lars Kai Hansen¹.

Abstract—EEG source reconstruction involves solving an inverse problem that is highly ill-posed and dependent on a generally fixed forward propagation model. In this contribution we compare a low and high density EEG setup's dependence on correct forward modeling. Specifically, we examine how different forward models affect the source estimates obtained using four inverse solvers Minimum-Norm, LORETA, Minimum-Variance Adaptive Beamformer, and Sparse Bayesian Learning.

I. INTRODUCTION

Electro-encephalography (EEG) holds great promise for functional brain imaging due to its high temporal resolution. In comparison with functional magnetic resonance imaging (fMRI) and positron emission tomography (PET), the slow hemodynamic response does not affect EEG. In addition fMRI and PET involve heavy scanner equipment and immobilization constraints that compromise the experimental situation, while EEG can be performed under much more natural conditions.

Today EEG based brain imaging suffers from a lack of spatial specificity due to the complex propagation of neural quasi-static electric fields to the array of sensors placed at the scalp surface. Motivated by the desire to perform reliable and precise reconstruction of the neural current density, much effort has been devoted to development of improved inversion methods. The current literature can be divided in two major approaches: Equivalent current dipole (ECD) and distributed models. In ECD methods [1] it is assumed that the brain activity is generated by a small number of focal sources, which restricts the source localization problem to a challenge of determining the positions and orientations of the ECDs. In distributed models several prior assumptions are made in order to solve the ill-posed inverse problem. For example l_2 -norm approaches, like the weighted minimum norm method [2] and low resolution electromagnetic tomography (LORETA) [3], assume sources to be diffuse and highly distributed. On the other hand models based on the l_1 -norm [4], l_p -norms [5], minimum variance beamformer [6], Bayesian model averaging [7], multiple priors models [8], and automatic relevance determination methods [9], [10], implement more focal sources. Most of these source

localization methods employ spatial-temporal priors in order to accommodate for the focal source distribution.

While the recent EEG imaging literature mainly have focused on the source reconstruction performance using high density EEG equipment we here draw the attention to quantify the performance of EEG brain imaging using few electrodes as we are interested in mobile EEG equipment. We have previously, demonstrated the feasibility of performing online brain imaging on a smartphone device [11] allowing for experiments in more naturalistic settings. We here seek a quantification of how well the current sources can be reconstructed when evaluating different forward models and source reconstruction methods.

Analyzing the importance of precise forward models and their influence on either the forward problem or the inverse problem is far from new to the EEG community. A number of contributions have already been published e.g. [12], [13]. A majority of the forward model investigations performed evaluates the forward models at sensor level or only examine a few dipoles located in different brain regions. These contributions have been of crucial importance to the EEG community as they have shed light on serious issues that we need to be aware of when the source solutions are used as the basis of conclusions in a given setup. In [12] an examination of the influence of geometric errors on the source estimates is performed using BEM models constructed from MR or CT images. A quite similar approach as the analysis above have been presented in [14]. The study in [14] deals with geometric errors introduced by using too simple head models (spheres) compared to more realistic BEM models. To evaluate the effect, angles between forward fields were examined when assuming no noise at the sensor level. In contrast to [14] we explored forward model uncertainties in face of noise present at the sensor level [15] and demonstrated that indeed source confusion is dependent on the interplay of forward field errors and the amount of noise present in the recordings.

Other types of uncertainties affecting the forward models are the specific tissue conductivity values and the importance of modeling specific tissues as anisotropic rather than isotropic have been discussed in [13], with the overall consensus that inaccurate modeling of the skull leads to significant error contributions on the sources. In fact [13], [16] states that a smearing effect on the forward potential computation is introduced by the skull anisotropy. The deeper

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a source is located the more it is surrounded by anisotropic tissues. Thus, electric fields generated by deeper sources are more affected by the anisotropy than superficial sources.

Of more recent studies [17] should be mentioned in which a careful analysis of how the number of electrodes, geometric errors (spheres versus FEM head models), and anisotropy versus isotropy affect the source estimates obtained by beamformers. To the authors knowledge this is the first study comparing how different inverse methods solutions are affected by different choices of forward models as well as the resolution with respect to the number sensors.

II. METHODS

The relation between the measured EEG signal and the brain's current sources can be expressed as a linear instantaneous form in the sources. The forward relation can be written as [18]

$$\mathbf{Y} = \mathbf{A}\mathbf{X} + \mathcal{E}, \quad (1)$$

where the measured EEG signal is denoted $\mathbf{Y} \in \mathbb{R}^{N_c \times N_t}$, the current sources $\mathbf{X} \in \mathbb{R}^{N_d \times N_t}$, and the noise \mathcal{E} is assumed additive. Number of channels, dipoles (or sources), and time samples are denoted N_c , N_d , and N_t , respectively. The coupling of sensors and the current sources is expressed through the lead field matrix/forward model $\mathbf{A} \in \mathbb{R}^{N_c \times N_d}$ with the rows referred to as the lead fields for the sensors and the columns as the forward fields for the sources. The forward model depends on sensor positions, a so-called 'head model' of the spatial distribution of tissue, and tissue conductivity values. Multiple methods based on the physical properties of the brain and Maxwell's equations are available for computing \mathbf{A} .

A. Minimum Norm and LORETA

Given the linear relation in Eq. (1) and if we assume the noise to be time independent Gaussian distributed, the observation model becomes $p(\mathbf{Y}|\mathbf{X}) = \prod_{t=1}^{N_t} \mathcal{N}(\mathbf{y}_t | \mathbf{A}\mathbf{x}_t, \beta^{-1}\Sigma_{\mathcal{E}})$ where $\Sigma_{\mathcal{E}}$ is the noise spatial covariance matrix. We here realize the source localization by a Bayesian formulation of the widely used minimum norm (MN) [2] and LORETA [3] methods as they allow fast computation of the inverse solution. With MN regarded as a special case of the LORETA we use as prior distribution for the sources a multivariate Gaussian $p(\mathbf{X}|\alpha) = \prod_{t=1}^{N_t} \mathcal{N}(\mathbf{x}_t | \mathbf{0}, \alpha^{-1}\mathbf{L}^T\mathbf{L})$ with \mathbf{L} being the Laplacian operator incorporating spatial smoothness on the source level. MN is obtained in the limit of no spatial smoothness, i.e. replacing $\mathbf{L} = \mathbf{I}$. Source estimates are now obtained from Bayes' rule by computing the posterior distribution over the sources, which leads to $p(\mathbf{X}|\mathbf{Y}) = \prod_{t=1}^{N_t} \mathcal{N}(\mathbf{x}_t | \boldsymbol{\mu}_t, \Sigma_x)$ with

$$\Sigma_x = \alpha^{-1}\mathbf{K} - \alpha^{-1}\mathbf{K}\mathbf{A}^T\Sigma_y\mathbf{A}\mathbf{K}\alpha^{-1} \quad (2)$$

$$\boldsymbol{\mu}_t = \alpha^{-1}\mathbf{K}\mathbf{A}^T\Sigma_y\mathbf{y}_t. \quad (3)$$

Here we have defined $\mathbf{K} \equiv \mathbf{L}^T\mathbf{L}$ and $\Sigma_y^{-1} \equiv \alpha^{-1}\mathbf{A}\mathbf{K}\mathbf{A}^T + \beta^{-1}\Sigma_{\mathcal{E}}$. Estimation of sources and the precision parameters α and β are carried out using a standard expectation-maximization (EM) scheme [19].

B. Beamforming

Here we use minimum-variance adaptive beamforming, which reconstructs the signal s_i of each dipole i by a spatial filter, $s_i = \sum_j W_{ij}y_j$. It chooses the filter that minimizes the noise variance in the reconstructed signal under a unit-gain constraint. Thus, for each i , we seek

$$\hat{W}_{ij} = \underset{\mathbf{W}}{\operatorname{argmin}} (\mathbf{W}\Sigma_{\mathcal{E}}\mathbf{W}^T)_{ii}, \quad (\hat{\mathbf{W}}\mathbf{A})_{ii} = 1. \quad (4)$$

The resulting reconstruction is given by

$$x_i = \frac{(\mathbf{A}^T\mathbf{C}_y^{-1}\mathbf{y})_i}{(\mathbf{A}^T\mathbf{C}_y^{-1}\mathbf{A})_{ii}} \quad (5)$$

where \mathbf{C}_y is the empirical data covariance. In dense EEG systems, where the number of sensors exceeds 100, this covariance is low-rank and must be suitably regularized. However, in systems with a small number of sensors, such as the one described here, regularization is usually not required.

C. Sparse Bayesian Learning (SBL)

SBL is a promising recent addition to the source analysis toolkit. In contrast to the previous methods which result in brain images with a rather low spatial resolution, SBL's images are very sparse. This sparseness is achieved by modeling each dipole distribution by a Gaussian with its own separate precision parameter α_i , $p(\mathbf{X}) = \prod_{t=1}^{N_t} \mathcal{N}(\mathbf{x}_t | \mathbf{0}, \mathbf{D}^{-1})$, where $\mathbf{D} = \operatorname{diag}(\alpha)$ leading to a posterior distribution

$$p(\mathbf{X}|\mathbf{Y}) = \prod_{t=1}^{N_t} \mathcal{N}(\mathbf{x}_t | \boldsymbol{\mu}_t, \Sigma_x) \text{ with}$$

$$\Sigma_x^{-1} = \mathbf{A}^T\beta\Sigma_{\mathcal{E}}^{-1}\mathbf{A} + \mathbf{D} \quad (6)$$

$$\boldsymbol{\mu}_t = \Sigma_x\mathbf{A}^T\beta\Sigma_{\mathcal{E}}^{-1}\mathbf{y}_t. \quad (7)$$

The precision parameters are estimated from data by a EM-like algorithm, made efficient using a convex optimization technique. The update rule for α is given in [9].

III. EMPIRICAL EVALUATION

We demonstrate the influence of the choices of forward models on the source estimates depending on which inverse method that is used. In order to validate how the inverse methods are affected by these choices we focus on two different EEG setups, Emotiv EPOC (16 channels) and Biosemi Active-II system (64 channels). For each of the EEG setups we examine three types of head models; 3-spheres (SPM8 toolbox), BEM-CP (SPM8 toolbox) [20], BEM-OP (OpenMEEG toolbox) [21] all using the same cortical surface with a resolution of 5,124 vertices. In contrast to spheres models BEM models face high numerical challenges in order to extract the forward fields at the cortical level. A limitation with the BEM-CP implementation is a risk of improper handling of forward fields for vertices very close to the inner skull. This issue is illustrated in Fig. 1 in which we demonstrate the 2-norm of each of the 5,124 vertices forward fields. We note that the BEM-CP has a number of vertices having forward fields much larger than the average. In this section we inspect how such discontinuities in the electric field may affect the source solutions.

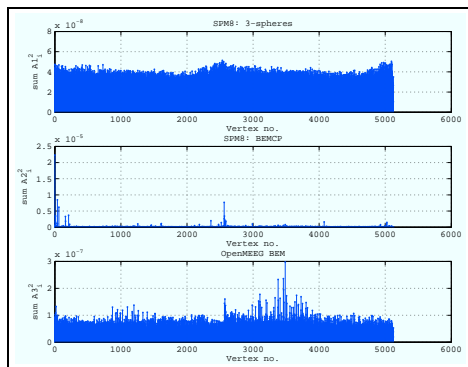


Fig. 1. The distribution of the squared 2-norm of the forward fields for three different forward models 3-spheres, BEM-CP, and BEM-OP when using 64-channel Biosemi layout.

Evaluation is carried out on synthetic data. We select a small cortical area in the right temporal lobe as being active and with a half sine as temporal signature. Fig.2.a shows the spatial distribution. As true forward propagation model we apply the OpenMEEG BEM model with tissue conductivities brain:skull:scalp = 0.33:0.0041:0.33S/m. Gaussian noise is added to the clean EEG signal in the order of SNR = 10, see Fig.2.b. We define SNR as the ratio between the power of the clean EEG and the noise. Fig.2.c shows the source solutions of MN, LORETA, MVAB, and SBL methods when applied to a low resolution setup of 16 channels (Emotiv) and high density 64-channels (Biosemi). Overall MN, LORETA, and MVAB all leads to widespread activity with MVAB having difficulties to capture the simulated source in the temporal lobe. MN seems to be more affected by the BEM-CP's discontinuities in the electric field for the Emotiv setup compared to Biosemi. However, LORETA minimizes the influence of these discontinuities by its spatial smoothness. The source estimates of the SBL algorithm on the other hand leads to highly sparse solutions with a few strong sources located close to the true source region.

IV. CONCLUSIONS

We examined inaccurate forward models influence on the source reconstruction in a low and high density EEG setup. Source solutions obtained using MN, LORETA, and SBL demonstrated possibility of recovering sources located in the temporal lobe at a SNR=10 reliable for most of the forward models and with SBL being the method resulting in the most consisting source estimates for the the different forward models. Further studies should evaluate the performance under lower SNRs and with multiple source regions being active simultaneously. Moreover, forward models considering anisotropy such as Finite Volume Model and Finite Element Model would be interested to include in the comparison.

REFERENCES

- [1] M. Scherg, T. Bast, and P. Berg, "Multiple source analysis of interictal spikes: Goals, requirements, and clinical value," *J. Clin. Neurophysiol.*, vol. 16, pp. 214–224, 1999.
- [2] M.S. Hämäläinen and R.J. Ilmoniemi, "Interpreting magnetic fields of the brain: minimum norm estimates," *Med. Biol. Eng. Comput.*, vol. 32, pp. 35–42, 1994.
- [3] R.D. Pascual-Marqui, M. Michel, and D. Lehmann, "Low resolution electromagnetic tomography: A new method for localizing electrical activity in the brain," *Int J. Psychophys.*, vol. 18, pp. 49–65, 1994.
- [4] M. Fuchs, M. Wagner, T. Kohler, and H.A. Wischman, "Linear and nonlinear current density reconstructions," *J. Clin. Neurophysiol.*, vol. 16, no. 3, pp. 267–295, 1999.
- [5] T. Auranen, A. Nummenmaa, M. Hämäläinen, I. Jääskeläinen, J. Lampinen, A. Vehtari, and M. Sams, "Bayesian analysis of the neuromagnetic inverse problem with ℓ^p -norm priors," *NeuroImage*, vol. 26, pp. 870–884, 2005.
- [6] F. Darvas, D. Pantazis, E. Kucukaltun Yildirim, and R. Leahy, "Mapping human brain function with MEG and EEG: methods and validation," *NeuroImage*, vol. 25, pp. 383–394, 2004.
- [7] N.J. Trujillo-Barreto, E. Aubert-Vazquez, and P.A. Valdes-Sosa, "Bayesian model averaging in EEG/MEG imaging," *NeuroImage*, vol. 21, no. 4, pp. 1300–1319, 2004.
- [8] K. Friston, L. Harrison, J. Daunizeau, S. Kiebel, C. Phillips, N. Trujillo-Barreto, R. Henson, G. Flandin, and J. Mattout, "Multiple sparse priors for the M/EEG inverse problem," *NeuroImage*, vol. 39, pp. 1104–1120, 2008.
- [9] D. P. Wipf, J. P. Owen, H. T. Attias, K. Sekihara, and S. S. Nagarajan, "Robust Bayesian estimation of the location, orientation, and time course of multiple correlated neural sources using MEG," *Neuroimage*, vol. 49, no. 1, pp. 641–655, 2010.
- [10] Carsten Stahlhut, Hagai T. Attias, David Wipf, Lars K. Hansen, and Srikantan S. Nagarajan, "Sparse spatio-temporal inference of electromagnetic brain sources," in *Machine Learning in Medical Imaging*, vol. 6357 of *Lecture Notes in Computer Science*, pp. 157–164. Springer Berlin / Heidelberg, 2010.
- [11] A. Stopczynski, J. Larsen, C. Stahlhut, M. Petersen, and L. Hansen, "A smartphone interface for a wireless eeg headset with real-time 3d reconstruction," *Affective Computing and Intelligent Interaction*, pp. 317–318, 2011.
- [12] G. Huiskamp, M. Vroeijsenstijn, R. van Dijk, G. Wieneke, and A.C. van Huffelen, "The need for correct realistic geometry in the inverse EEG problem," *IEEE Trans. Biomed. Eng.*, vol. 46, no. 11, pp. 1281–1287, November 1999.
- [13] C.H. Wolters, A. Anwander, X. Tricoche, D. Weinstein, M.A. Koch, and R.S. MacLeod, "Influence of tissue conductivity anisotropy on EEG/MEG field and return current computation in a realistic head model: A simulation and visualization study using high-resolution finite element modeling," *Neuroimage*, vol. 30, no. 3, pp. 813–826, 2006.
- [14] M. Fuchs, R. Drenckhahn, H. Wischmann, and M. Wagner, "An improved boundary element method for realistic volume-conductor modeling," *IEEE Transactions on Biomedical Engineering*, vol. 45, no. 8, pp. 980–997, 1998.
- [15] Carsten Stahlhut, *Functional Brain Imaging by EEG: A Window to the Human Mind*, Ph.D. thesis, Technical University of Denmark, DTU Informatics, DK-2800 Richard Petersens Plads, Denmark, 2011.
- [16] H. Hallez, B. Vanrumste, R. Grech, J. Muscat, W. De Clercq, A. Vergult, Y. D'Asseler, K.P. Camilleri, S.G. Fabri, S. Van Huffel, et al., "Review on solving the forward problem in EEG source analysis," *J of NeuroEng. and Rehab.*, vol. 4, no. 1, pp. 46, 2007.
- [17] O. Steinsträter, S. Sillekens, M. Junghoefer, M. Burger, and C.H. Wolters, "Sensitivity of beamformer source analysis to deficiencies in forward modeling," *Human brain mapping*, vol. 31, no. 12, pp. 1907–1927, 2010.
- [18] S. Baillet and L. Garnero, "A bayesian approach to introducing anatomo-functional priors in the EEG/MEG inverse problem," *IEEE Trans. on Biomedical Engineering*, vol. 44, no. 5, pp. 374–385, 1997.
- [19] C. M. Bishop, *Pattern Recognition and Machine Learning*, Springer, NY 10013 (USA), 2006.
- [20] C.L.M. Phillips, "Source estimation in EEG: Combining anatomical and functional constraints," *PhD Thesis*, 2000.
- [21] A. Gramfort, T. Papadopoulos, E. Olivi, M. Clerc, et al., "Openmegg: opensource software for quasistatic bioelectromagnetics," *Biomedical engineering online*, vol. 9, no. 1, pp. 45, 2010.

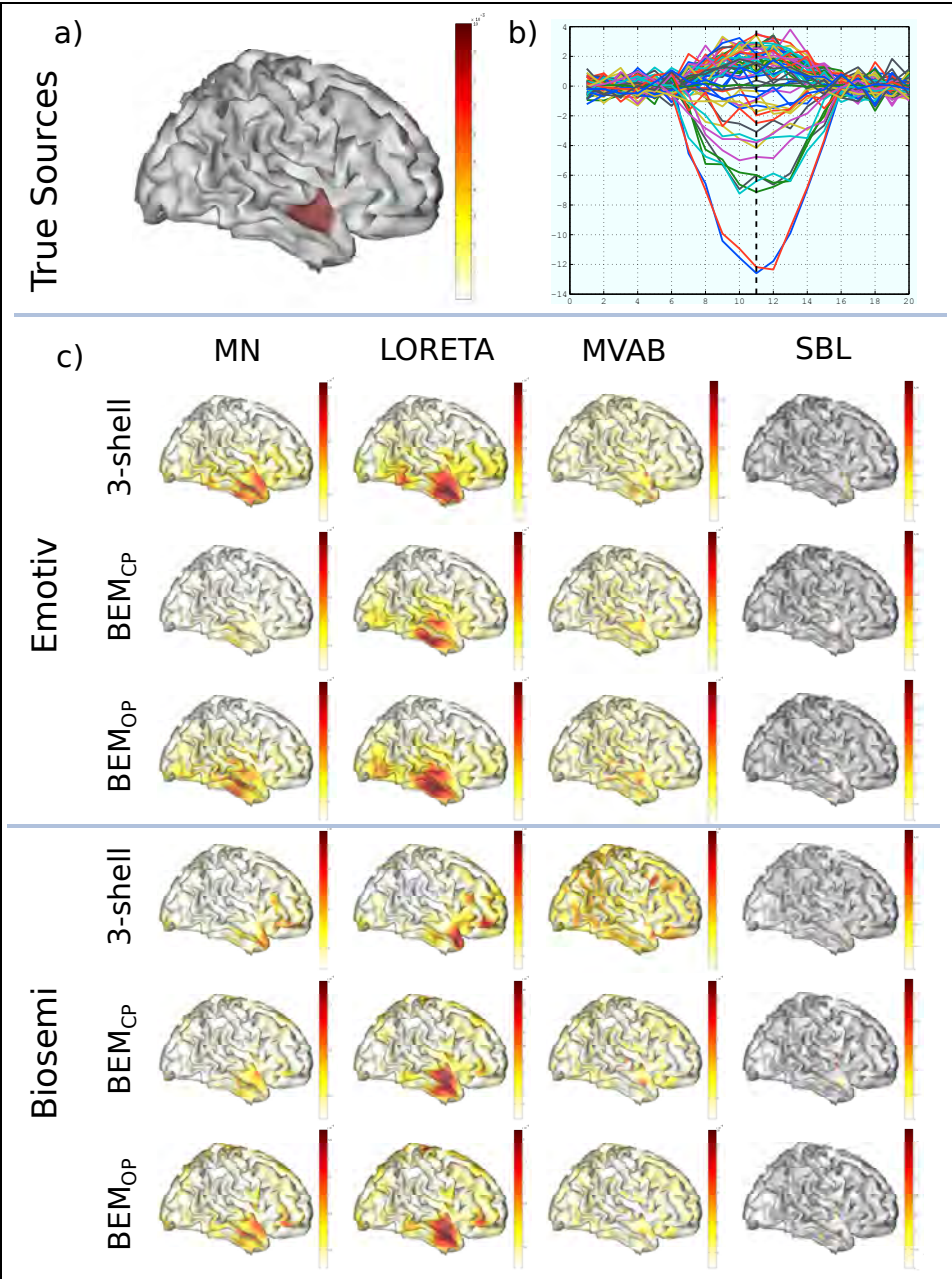


Fig. 2. a) Simulated spatial source distribution. b) Simulated sensor signal including noise. c) Reconstructed source estimates using MN, LORETA, MVAB, and SBL on two different EEG setups, Emotiv ($N_c = 16$) and Biosemi ($N_c = 64$) and three head models: 3-shell, BEM-CP, and BEM-OP.

APPENDIX H

Privacy in Sensor-Driven Human Data Collection

Arkadiusz Stopczynski, Riccardo Pietri, Alex Pentland, David Lazer, and Sune Lehmann.
Privacy in Sensor-Driven Human Data Collection: A Guide for Practitioners. *Upcoming paper*
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Privacy in Sensor-Driven Human Data Collection:
A Guide for Practitioners
Working Paper

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Contents

| | | |
|-------|---|----|
| 1 | Introduction | 2 |
| 2 | Sensor-Driven Human Data Collection in Academia | 5 |
| 2.1 | Smaller frameworks | 5 |
| 3 | Informed Consent | 6 |
| 3.1 | Understanding | 8 |
| 3.2 | Control | 9 |
| 3.3 | Living Informed Consent | 9 |
| 3.4 | Living Informed Consent and Reproducibility | 11 |
| 4 | Data Security | 12 |
| 4.1 | Common Solutions | 12 |
| 4.2 | Distributed Architecture | 13 |
| 5 | Privacy and Datasets | 14 |
| 5.1 | Privacy Implementations | 15 |
| 5.1.1 | Noise | 15 |
| 5.1.2 | Anonymization | 16 |
| 5.1.3 | Homomorphic Encryption | 16 |
| 5.2 | Attacks against Privacy | 17 |
| 6 | Information Ownership and Disclosure | 19 |
| 6.1 | Sharing | 19 |
| 6.1.1 | Sharing with other users | 19 |
| 6.1.2 | Sharing with researchers | 20 |
| 6.2 | Data Control | 20 |
| 6.2.1 | Information Flow Control | 20 |
| 6.2.2 | Data Expiration | 22 |
| 6.2.3 | Watermarking | 23 |
| 6.2.4 | Contract Governance | 24 |
| 7 | Privacy Actionable Items | 26 |

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Abstract

In recent years, the amount of information collected about human beings has increased dramatically. This development has been partially driven by individuals posting and storing data about themselves and friends using online social networks (such as Facebook or Twitter) or collecting their data for self-tracking purposes (quantified-self movement). Data regarding human behavior is also collected through the environment, embedded RFIDs, cameras, traffic monitoring, business transactions, etc.. Across the sciences, researchers conduct studies collecting data with an unprecedented resolution and scale. Using computational power combined with mathematical models, such rich datasets can be mined to infer underlying patterns, thereby providing insights into human nature.

Much of the data collected is sensitive. It is private in the sense that most individuals would feel uncomfortable sharing their collected personal data publicly. For this reason, the need for solutions to ensure the privacy of the individuals generating data has grown alongside the data collection efforts. Out of all the massive data collection efforts, this paper focuses on efforts directly instrumenting human behavior, and notes that—in many cases—the privacy of participants is not sufficiently addressed. For example, study purposes are often not explicit, informed consent is ill-defined, and security and sharing protocols are only partially disclosed.

This paper provides a survey of the work related to addressing privacy issues in research studies that collect detailed sensor data on human behavior. Reflections on the key problems and recommendations for future work are included. We hope the overview of the privacy-related practices in massive data collection studies can be used as a frame of reference for practitioners in the field. Although focused on data collection in an academic context, we believe that many of the challenges and solutions we identify are also relevant and useful for other domains where massive data collection takes place, including businesses and governments.

1 Introduction

Humanity is recording the minute-to-minute details of human behavior and interaction at an unprecedented rate. The datasets come from diverse sources such as user-generated content in online social networks (e.g. Twitter, Facebook) and on other online services (e.g. Flickr, Blogger); human communication patterns recorded by telecom operators and email providers; customer information collected by traditional companies and online wholesalers (e.g. Amazon, Target); data from pervasive environments such as sensor-embedded infrastructures (e.g. smart houses); social science experiments; the list continues.

As technology advances, the technical limitations related to storing and sharing these collections of information are gradually overcome, providing the opportunity to collect and analyze these digital traces. This ever-increasing volume of user-generated content carries significant economic and social value and, as such, is of interest for business organizations, governmental institutions, and social science researchers.

Massive data collection efforts happen in virtually every aspect of the modern world; businesses, governments, and research institutions collect and mine data. In many cases, this may not raise directly actionable privacy concerns. Data may be publicly available, for example in the form of Twitter posts. Or it may be owned and tightly controlled by a company, such as Call Detail Records (CDRs) collected by telecom operators. Often, however, when data are collected by directly instrumenting human behavior, there is a need to ensure the privacy of the participants.

For the research community, the data revolution has had an impact that can hardly be underestimated. Data persistence and searchability combined with enhanced computational power has given rise to Computational Social Science (CSS), a domain of interdisciplinary research that gathers and mines large-scale behavioral datasets to study human behavior and social interactions [1–3]. In this paper we focus on the sensor-driven massive data collection efforts with human subjects for research purposes, as practiced in computational social science. Many of the challenges and solutions stated here translate,

however, to other domains, such as classical social science or data collection in a business or governmental context.

Protecting the wellbeing of the participants of the studies in any domain is of utmost importance. The trust that exists between the participants and the researchers is even more difficult to establish and maintain when the amount and resolution of the collected data increases. The more sensitive the data is, the more disastrous the consequences of misuse can be. Protecting the privacy of the participants is driven by the ethics and responsibility of individual researchers; the risks are to the collective scientific endeavor, there is an issue of public confidence in the conducted research. As we rapidly collect more and more data, even a single case of data abuse could lead to a loss of public confidence and — as a consequence — a decreased ability to carry out studies. This is why we recommend a set of standards and tools for responsible management of privacy that can be easily deployed and used as more researchers join the big data movement.

Protecting human subjects is not a new idea. Different research domains, countries, and institutions have their own means of ensuring proper treatment of human subjects. In the United States, studies involving human subjects are regulated by the Institutional Review Boards (IRBs). These academic committees are designated to approve, monitor, and review any medical and non-medical research involving humans. Part of the review process is an assessment of the informed consent procedure, ensuring that the participants are properly informed about the study. The IRBs also provide guidelines for data confidentiality, such as removing identifying information, ensuring data deletion, or secure storage of the data.

However, as the collected data sets grow larger, more complex, and of higher resolution, the typical approach to treatment of human subjects may be insufficient. Proper handling of massive data, informing and obtaining users' authorizations, ensuring privacy when performing data analyses; all these problems, although not new, become qualitatively more difficult to handle when the data become big. We are seeing the dawn of studies that are regulated by the IRBs and corresponding bodies in other countries, but use methods which the IRBs are not proficient in assessing. For example, in many of the research studies collecting massive amounts of data from human subjects, the data are accessed and analyzed in almost-real time, making it difficult to apply de-identification techniques that operate on the static datasets. Similarly, simply conveying the message to the participants about the study goals and scope can become a challenge, as the contact between the researchers and users decreases due to the scale of studies or the enrollment procedure, while the complexity of the data and subsequent analysis increases. This poses a potential problem for the research community wanting to do massive data collection on human subjects—studies that require IRB approval—when the IRB guidelines may not necessarily be suitable for such studies.

While classical social science studies primarily use questionnaires and interviews for data collection, many CSS studies use sociometric badges [4] or smartphones [5–7] to sense, collect, and transmit large quantities of multi-purpose data. Data collected from sensors include WiFi and Bluetooth IDs of the surrounding devices, GPS traces, SMS and call logs. Data are also collected from online services (Facebook, Twitter), both from public streams and from users' accounts, based on their authorizations. While such a longitudinal approach allows scientists to maintain a broad scope, the scale and accuracy of the collected data often results in large amounts of sensitive information about the users, which may lead to privacy concerns. Additionally, the sensitivity of the sensor data may be latent; it is not clear to the users why their location or social data need to be protected. We note that data of similar sensitivity has been historically collected in the health and biomedical fields, with collection of blood samples, brain scans, or genetic material. With the development of online services such as *23andMe* (<https://www.23andme.com/>) or *patientslikeme* (<http://www.patientslikeme.com/>) and large available databases of medical data [8], the medical data privacy concerns are very similar to the sensor-driven human data on which we are focusing this article.

To a large degree, the public is unaware of the potential problems associated with sharing sensitive

data. This lack of awareness is revealed in a number of contexts, for example via a documented tendency to ‘trade privacy for services’ [9], or displaying carelessness regarding possible risks [10, 11]. It has been shown that while many users are comfortable with sharing daily habits and movements through multiple applications, only a minority of them are aware of which parties are the recipients of this information. Concurrently, pinpointing sensitive information about others is becoming easier using powerful search engines such as Google, Facebook Graph Search, or smartphone mashup apps (e.g. Girls Around Me, <http://girlsaround.me/>).

To further aggravate this scenario, it has been shown that many of the techniques employed so far to protect users’ anonymity are flawed. Scandals such as re-identification of users in the *Netflix Prize* data set [12] and similar breaches [13, 14] show that simple de-identification methods can be reversed to reveal the identity of individuals in those data sets [15]. Attackers can also use these re-identification techniques to perpetrate so-called ‘reality theft’ attacks [16].

In order to avoid such a negative scenario and to maintain and increase the trust relation between research community and participants, the scientific community must reconcile the benefits of their research with respect for users’ privacy and rights. The current situation in the field is a heterogeneous set of approaches that raise significant concerns: study purposes are often not made explicit, the implementation of informed consent is often problematic, and in many cases, security and sharing protocols are only partially disclosed.

As the number of participants and the duration of the studies increase, the pre-existing relation between researchers and participants grows weaker. Today, the participants in the largest deployments of the studies with human subjects are still students from a particular university, members of a community, or friends and family of the researchers. Studies that are open to the public allow for participants with no prior relation to the researchers. While this change certainly ameliorates some privacy concerns, it also lessens the personal investment in the wellbeing of study participants. As a consequence, ensuring good practices in informing those participants about their rights, the consent they express, the incentives etc. becomes even more important.

In a modern context, privacy implies that individuals should be able to determine how much personal information can be disclosed, to whom, and how it should be maintained and disseminated [17, 18]. Concurrently, we acknowledge that what is considered to be personal information – and what is not – changes among cultures, individuals, time, place, audience, and circumstances. Thus, the notion of privacy is dynamic, depends on context, and may change, for example as people discover that disclosing their private information may lead to value in return [19].

Providing adequate privacy for the participants in massive data collections studies, especially in a research context, is important. We recognize that there are additional factors to consider in the design of studies, such as reproducibility, cost, reliability, and impact on the third parties. It is important to find the right balance between all these aspects, which may not always be easy. Although it may seem paradoxical, we see better privacy measures as a means for allowing more data to be collected, analyzed, and shared. Users who feel confident about providing access to their data and see more value in doing so, will result in availability of even larger and more comprehensive datasets.

Our contributions in this paper are two-fold. First, we provide an overview of the privacy-related practices in existing sensor-driven human data collection studies. We have selected representative works in the field and analyzed the fundamental privacy features of each one. We focus on studies involving instrumentation of humans, where the data collection is sensor-driven and performed on a massive scale. We include the consent-based collection of data from online social networks (OSNs), and additional sources, such as questionnaires, where such data augment the data collected from sensors. Such collection efforts raise distinct issues around security, consent, and sharing. The result is a longitudinal survey that we intend as a frame of reference for current and future practitioners in the field. Second, we lay the groundwork for a *privacy management change process*. Using the review as a starting point, we have constructed a list of the most important challenges to overcome for the studies: we call these *privacy*

actionable items. For each item, we delineate realistic implementations and reasonable life-spans. Our goal is to inspire introspection and discussion, as well as to provide a list of concrete items that can be implemented today and that overcome some of the problems related to the current privacy situation. The intended audience are researchers and scholars engaging in sensor-driven human data collection. We intend many of the reviewed practices and suggestions provided to generalize to other domains, such as data collection in companies or other types of data.

2 Sensor-Driven Human Data Collection in Academia

We broadly categorize the projects selected for our privacy survey into two families: generic frameworks and specialized applications. The former category contains systems that collect a variety of different data streams deployed for the purposes of studying human behavior in longitudinal studies. The second category consists of applications that collect sensor data for a specific, well-defined purpose.

Human Dynamics Group *Friends and Family* is a data collection study deployed by the Massachusetts Institute of Technology (MIT) in 2011 to perform controlled social experiments in a graduate family community [20]. For the purpose of this study, researchers collected 25 types of signals (e.g. wireless network names, proximity to Bluetooth devices, statistics on applications, call and SMS logs) using Android smartphones as sensors. *Funf* – the mobile sensing framework developed for this study – is the result of almost a decade of studies in Media Lab Human Dynamics Group on data-collection using mobile devices. In 2008 a Windows Mobile OS [21] app was used to collect data from students and study connections between behavior and health conditions (e.g. obesity), and to measure the spread of opinions. Four years before that, a team from Media Lab studied social patterns and relationships in users' daily activities, using Nokia phones [22]. In 2003 a Media Lab team pioneered the field by developing the first sensing platform [23] in order to establish how face-to-face interactions in working environments influence the efficiency of organizations. While purposes of the studies and mobile sensing technologies have evolved, the general setup with a single server to collect and store the data coming from the devices, has generally remained unchanged.

OtaSizzle Another large-scale data-collection effort was conducted by Aalto University researchers in 2011 [24]. Here, the focus was on understanding social relations by combining multiple data sources. The results showed that in order to better describe social structure, different communication channels should be considered. Twenty students at the university were recruited by email invitation and participated in the experiment for at least three months. The research platform involved three different data sources: text messages, phone calls (both gathered with Nokia N97 smartphones), and data from an experimental OSN called *OtaSizzle*, hosting several social media applications for Aalto University. All the gathered information was temporarily stored on the smartphones, before uploading to a central server.

Lausanne The last framework that we include here is the *Lausanne Data Collection Campaign (LDCC)* [25–27], conducted by the Nokia Research Center in collaboration with the EPFL institute of technology between 2009 and 2011. The purpose was to study users' socio-geographical behavior in a region close to Lake Geneva. The LDCC platform involved a proxy server used to collect raw information from phones, anonymizing the data before transferring them to a second server for research purposes.

2.1 Smaller frameworks

Below we present an overview of three groups of specialized platforms and smartphone applications developed by research groups for different purposes. In Table 1 we present distributed architecture frameworks. Table 2 shows projects related to the creation of privacy policies and management. In Table 3

we present applications that generate, collect, and share information about users, using smartphones as sensing devices. Other frameworks are also cited to provide useful examples. We remark that it is not our interest to discuss the primary goals of the mentioned studies (incentives, data mining algorithms, or results), but to present an overview of architectures, procedures and techniques employed for data collection and treatment—with specific focus on privacy.

| Name | Purpose | Privacy measures |
|--|--|--|
| Vis-a'-Vis [28] 2011 - Duke University, AT&T Labs | A personal virtual host running in a cloud computing infrastructure and containing users' (location) information. | Allows users to manage their information directly from their virtual host with full control; exposes <i>unencrypted</i> data to the storage providers. |
| Confab [29] 2004 - University of California at Berkeley, University of Washington | A distributed framework facilitating development of other privacy-aware applications for ubiquitous computing. | Personal data is stored in computers owned by the users, providing greater control of information disclosure. |
| MyLifeBits [30, 31] 2001 - Microsoft Research | Early example of digital database for individuals' everyday life, recording and managing a massive amount of information such as digital media, phone calls, meetings, contacts, health data etc. | Information kept in SQL databases. Privacy concerns mentioned but <i>not</i> addressed in the project. |
| VPriv [32] 2009 - MIT, Stanford University | Privacy-aware location framework for car drivers, producing an anonymized location database. Can be used to create applications such as usage-based tolls, automated speeding tickets, and pay-as-you-go insurance policies. | <i>Homomorphic encryption</i> [33], ensures that drivers' identities are never disclosed in the application. |
| HICCUPS [34] 2009 - University of Massachusetts Amherst | A distributed medical system where a) physicians and caregivers access patients' medical data; b) researchers can access medical aggregate statistics | Implements homomorphic encryption techniques to safeguard patients' privacy. |
| Darwin [35] 2010 - Dartmouth College, Nokia | A collaborative framework for developing a variety of sensing applications, such as place discovery or tagging applications. | Provides distributed machine learning algorithms running directly on smartphones. Raw data are not stored on and do not leave the smartphone. |
| AnonySense [36, 37] 2008 - Dartmouth College | An opportunistic framework for applications using multiple smartphones to accomplish a single sensing task. | Provides anonymity to the users deploying k -anonymity [38]. |

Table 1. *Distributed frameworks.* The *Vis-a-Vis*, *Confab*, and *MyLifeBits* frameworks are personal information collectors that play the roles of users' virtual aliases. Two implementations of homomorphic encryption for drivers and healthcare follow. Finally, *Darwin* and *AnonySense* are collaborative frameworks.

3 Informed Consent

Here we examine how the state-of-the-art massive data collection studies involving human subjects approach the participants' understanding of the consequences of data collection, as well as their ability to control and access personal data during and after such studies.

| Name | Purpose | Privacy measures |
|--|---|---|
| PViz [39] 2012 - University of Michigan | A graphical interface that helps users of social networks with policy comprehension and privacy settings. | Nodes represent individuals and groups, different colors indicate the respective visibility. |
| Virtual Walls [40] 2007 - Dartmouth College, University of St Andrews | A policy language that leverages the abstraction of physical walls for building privacy settings. | Three levels of granularity ("wall transparencies") allow users to control quality and quantity of information disclosure towards other digital entities (users, software, services). |
| A policy-based approach to security for the semantic web [41] 2003 - University of Maryland Baltimore Country | A distributed alternative to traditional authentication and access control schemes. | Entities (users or web services) can specify their own privacy policies with rules associating credentials with granted rights (access, read, write, etc.). |

Table 2. *Policy frameworks.* An overview of tools that help users to understand and control their policy settings.

| Name | Purpose | Privacy measures |
|--|--|---|
| CenceMe [42] 2008 - Dartmouth College | Uses smartphones to sense peoples' activities (such as dancing, running, ...) and results are automatically shared on Facebook. | As soon the classification is performed on the devices the data is erased. |
| GreenGPS [43] 2010 - University of Illinois | A GPS navigation service which discovers <i>greener</i> (fuel-efficient) paths through drivers participatory collaboration (based on the previous framework <i>Poolview</i> [44]). | No fine-grained data control: if users feel the need for privacy, they need to switch off the GPS device to stop data collection. |
| Speechome Recorder [45, 46] 2012 - MIT, Northeastern University | An audio/video recording device for studying children's daily behavior in their family house. | Ultra-dense recordings temporarily kept locally and uploaded to central server. Scarce information about data encryption and transport security protocols are provided. |
| Cityware [47] 2008 - University of Bath | Application for comparing Facebook social graph against real-world mobility traces detected using Bluetooth technology. | Switching Bluetooth to invisible as a way to protect users' privacy. |
| FriendSensing [48] 2009 - MIT, University College London | Bluetooth used to suggest new friendships evaluating device proximities. | Same as <i>Cityware</i> . |
| FollowMe [49] 2010 - Massachusetts Institute of Technology | Service that uses HTTP and Bluetooth to automatically share indoor position (malls, hospitals, airports, campuses). | Implements a decentralized architecture to improve users' location privacy. |
| Locaccino [50] 2010 - Carnegie Mellon University | A mobile sharing system created to study peoples' location privacy preferences. | Relevant privacy considerations will be reported later in the article. |
| Bluemusic [51] 2008 - RWTH Aachen, University of Duisburg-Essen | Application developed for studying personalization of public environments. It uses Bluetooth <i>public</i> usernames as pointers to web resources that store users preferences. | Same as <i>Locaccino</i> . |

Table 3. *Applications.* Although providing great functionality for the users, the privacy-oriented settings for the user are often not sufficiently implemented.

In academic studies, informed consent consists of an agreement between researchers and the data producer (user, participant) by which the latter confirms she understands and agrees to the procedures applied to her data, including collection, transmission, storing, sharing, and analysis. The intention of the informed consent is to protect individual autonomy, ensure voluntary participation, and for the users to comprehend which information will be collected, who will have access to that information, what the

incentive is, and for what purposes the data will be used [52, 53]. In all studies the research ethic has a central role in relation to protecting the privacy of participants. For this reason, to be able to perform analyses on the collected data, scientists typically work under agreements defining allowed uses [24, 27].

The informed consent procedure was introduced in the Nuremberg Code following the revelations of torture by Nazi doctors during World War II [54]. Originally conceived for medical studies, informed consent has since been studied from the moral, ethical, philosophical, psychological, or practical point of view [55, 56], understood as a cornerstone of the rights of patients and subjects. Informed consent imposes legal obligations on the researchers, covering researcher-participant or doctor-patient relationship, use of consent forms, refusal of treatment, or participation in the research [57]. Protecting personal privacy is meant to protect individuals against stigmatization and discrimination, as well as various forms of social control which may undermine personal autonomy and democracy itself [53, 55]. To be specific, there are many ways in which abuses might be directly targeted—from imposing higher insurance rates based on individual shopping history [?] or creating problems for society as a whole, by limiting users’ choices and enclosing them in information bubbles [?].

In the sensor-driven human data collection studies, we note the scarcity of published informed consent procedures; the majority of the studies we reviewed have not published their consent procedures [2, 3, 20, 21, 42, 49, 58–60]. Due to this, it is difficult to produce comparisons and to create templates applicable for future studies. Where the procedures for achieving informed consent are reported, the agreement was carried out using forms containing users’ rights (similar to http://green-way.cs.illinois.edu/GreenGPS_files/ConsentForm e.g [21, 22, 24, 26, 43, 61]) or by accepting the terms of use during the installation of an application.

3.1 Understanding

Presenting extensive information about a study does not guarantee that informed consent has been implemented successfully: years of End-User License Agreements (EULAs) and other lengthy legal agreements show that most individuals tend to blindly accept forms that appear before them and to unconditionally trust the validity of the default settings which are perceived as authoritative [?, ?, 62]. The problem of understanding the consent procedure has been extensively studied in the medical context. Cassileth et al. in 1980 explored how much patients understand and are able to recall the information presented on the consent forms and in oral explanation, finding that only 60 percent of the participants understood the purpose and nature of the procedure [63]. The patients in the study believed that the consent forms were meant to “protect the physician’s rights” and authors concluded that, even with comprehensible forms, the legal connotations led to cursory reading and inadequate recall. A study of readability of the informed consent forms in 2003 found that on the FleschKincaid scale (0 - 12 US grade level) the average readability score for text provided by the IRBs was 10.6, with 95% falling into the 10.3 - 10.8 interval [64]. At the same time, among the 61 schools that specified explicitly grade-level standard for their forms, only 8 percent met this standard; the average readability score exceeded the stated standard by 2.8 grade levels. This indicates potential issues in how well the participants can comprehend the text they are signing, based on language comprehension alone, without even considering required domain-specific knowledge. Sugerman et al. reviewed in [65] the informed consent procedures for older adults, concluding that older age and fewer years of education contributed to decreased understanding of the consent form.

Various means of improving the understanding of the consent and making it truly informed have been researched, primarily in the clinical context. Lavori et al. explored in [66] the possibility and challenges of improving informed consent based on experimentation in ongoing clinical trials with respect to ethical, organizational, conceptual, and technical aspects. Evaluating how people understand their privacy conditions can be done, for example, by conducting feedback sessions throughout the duration of the experiment [26, 51]. One improvement could be to allow users to gradually grant permission over time, but the efficacy of this approach is not clear: some studies have shown that users understand the issues about security and privacy more clearly when the requests are presented gradually [67], while others argue that too many warnings distract users [40, 68, 69]. Flory and Emanuel presented a comprehensive

review of the methods that can be used to improve the understanding of the consent in [70]. They found that in the clinical context, participants may frequently not understand the disclosed information; one of the requirements of a well-implemented informed consent procedure [71,72]. To improve the consent procedure, they point out that the multimedia augmentation or replacement of the consent form can significantly improve participants' understanding; the effect is most pronounced in the group of mentally ill patients [73,74], although not always manifesting in the general population [75,76]. These results suggest that in the examined (clinical) context, basic comprehension of the form was not the problem, but rather higher-level reasoning about the information presented. Similarly, the effect of simplification of the consent forms is not clear, and depends to a large extent on whether the form is the only source of information for the participant. The most effective measure to improve understanding seems to be person-to-person contact and discussion about the research scope, purpose, procedures etc. Although this result is not surprising, in the context of this article the usefulness of such person-to-person interventions is limited; with hundreds and thousands of participants in the massive sensor-driven data collection, explaining the study to each one of them may simply not be feasible.

3.2 Control

In most cases, the current informed consent techniques represent an all-or-nothing approach that does not allow the user to select subsets of the permissions, making it only possible to either participate in the study fully or not at all [68]. Accounting for cases where the user are only to contribute subsets of the data is usually done by allowing to skip questions in the questionnaires or decline to participate in the optional elements of the study [20]. Generally, once the consent is granted by the user, her data contribution to the dataset becomes the property of the researchers, in that they can analyze, modify, or redistribute the data as they see fit, depending on the terms of the consent, but typically simply provided that basic de-identification is performed. As we suggest in the section called Information Ownership and Disclosure, it is a good practice for the researchers to clarify the sharing schemes and expiration of the collected information to the participants: if users cannot follow the flow of their data, it is difficult to claim that truly informed consent has been expressed. Since so little is understood about the precise nature of conclusions that may be drawn from high-resolution data, it is important to continuously work to improve and manage the informed consent as new conclusions from the data can be drawn. One option is that the paradigm should evolve from a one-time static agreement to dynamic consent management [77]. Furthermore, the concerns related to privacy are context-specific [50,78] and vary across different cultures [51,79]. In the literature, the need for a way to let the users easily understand and specify which kinds of data they would like to share and under what conditions was foreseen in 2002 by the W3C group, with the aim to define a Platform for Privacy Preferences (P3P) (suspended in 2006), in 2003 by Kagal et al. [41], and also in 2005 by Friedman et al. [52], all shaping dynamic models for informed consent. Recent studies such as [80] have worked to design machine learning algorithms that automatically infer policies based on user similarities. Such frameworks can be seen as a mixture of recommendation systems and collaborative policy tools in which default privacy settings are suggested to the user and then modified over time.

3.3 Living Informed Consent

We propose the term *Living Informed Consent* for the aligned business, legal, and technical solutions whereby the participant in the study is empowered to understand the type and quality of the data that is being collected about her, not only during the enrollment, but also as the data is being collected, analyzed, and shared with third parties. Rather than a pen and clipboard approach for the user enrollment, participants should expect to have a virtual space (a website or application) where they can change their authorizations, drop-out from the study, request data deletion, as well the ability to audit who is analyzing their data and how frequently their data are accessed.

As the quantity and quality of the data collected increase, it becomes difficult to claim that single-sentence description of *we will collect your location* truly allows the participant to realize the complexity of the signal collected and possible knowledge that can be extracted from it. For example, even a very small number of data points, such as location updates, can uniquely identify a participant, as has been shown in [15]. For this reason, access to the extracted high-level features of the data should be favored, as outlined in the openPDS approach [81]. High-level features are not only inherently better for privacy, as they limit the possible non-authorized uses of the data, they also make the authorization process easier for the user to comprehend (e.g. rather than agreeing to share location data, the user can agree to share the cities she visits, or average distance traveled per hour). Such an engaging approach to the users' consent will also be beneficial for the research community because as the relation with the user in terms of their consent expression extends beyond initial enrollment, the system proposed here makes it possible for the user to sign up for the new studies and donate their data from the previous studies.

The concept of Living Informed Consent is compatible with the discussion that has recently started around the need for improvements in the consent procedures; primarily in the biomedical research. Laura Siminoff pointed out in [82] a troubling lack of research and dialog around informed consent. A growing number of practitioners adopt the belief that current procedures are but an illusion of giving control to the users. In similar spirit, Erika Check Hayden discussed in [83] how the informed consent procedures are today broken: not giving participants sufficient control over their data and participation and not including the future developments allowing us to extract more from the data. At the same time the bureaucracy around obtaining the consent is growing to be an obstacle for high-quality research. Even the issue of sharing the results back to the participants is not straightforward; patients should have the option not to learn the results of research that was done on their data, such as genome. The reuse of the data for different research is challenging; data from the participants either become part of large datasets maintained by researchers, where users effectively lose control over them, or data can only be used for particular analysis, specified in the consent. Erika Hayden concludes that we can expect approaches allowing participants to control and track how researchers use their data. The same topic has been the focus of the Editorial in Nature vol. 486 entitled *Time to open up* [84]. Addressing the problem of broken consent procedure in biomedical studies, the article calls:

Technology and some creative thinking should be able to provide a solution to this problem. In an era when people can control who sees what types of personal information on their Facebook page, programmers should be able to design similar tools to give research volunteers a degree of influence over who uses their data and for which types of research.

Lunshof et al. propose in [85] an opposite approach to solve the same problem in the field of genomics. Rather than pushing for more end-user control, their thesis is that true confidentiality is impossible, due to the inherent uniqueness of the data. In their *Open Consent* the authors propose that volunteers will consent to unrestricted re-disclosure of data and disclosure of the gained knowledge, even if it cannot be predicted what can be learned from the data at the time of consent. The consent does not invoke promises of anonymity, privacy, or confidentiality, as those properties are impossible to truly guarantee for the dataset. Instead, the use of the data and disclosure practices should be based on ethics and the principle of veracity, backed by the reputation of researchers and their institutions. While the volunteers can request the deletion of their data, no guarantees are given about full removal, as the data might have contributed to published work, that cannot easily be reversed (see our discussion in the Living Informed Consent and Reproducibility section). Open Consent is used in the *Personal Genome Project*, in which the participants are considered informed volunteers, willing to give up their privacy for the public good, a practice causing some controversy [86].

The Living Informed Consent approach we propose, is aimed for the data that is most valuable when accessed in real-time and continuously: mobility patterns, health state, social activity. For such data we may not want to operate on frozen, aging datasets; instead we access fresh data, both for

research purposes and to build applications feeding information back to the participants, either as a behavior-change mechanism or to provide value for participation. Rather than clinical practice, where it is feasible and clearly beneficial to engage in person-to-person explanation of the research process, in sensor-driven massive data collection the participants may be too separated from the researchers to make such procedures feasible. At the same time, the expectations of the participants on sensor-driven studies are generally lower when compared to clinical research; the problem of participants' vulnerability and pressure to join the research is significantly smaller. For these reasons, we see Living Informed Consent, backed up by technical solutions such as openPDS as a viable framework for addressing the rising problems of consent procedure.

3.4 Living Informed Consent and Reproducibility

Giving the participants full control over their data can cause concerns about research replicability and reproducibility. If the data can change at any time, either because users modify or delete them, the results published on the basis of the data become impossible to replicate. One possible solution is to 'freeze' the data used for each publication, freezing precisely the data needed to replicate the published results. The issue of replicability must be addressed by the Living Informed Consent procedure. As with all the other data access, the freezes of the data—or preferably the relevant features needed to replicate the results—should be done subject to user authorizations, but once a freeze is done, the data must remain unchanged. Thus, for example, users may still request the deletion of their newer data, but cannot request modifications or deletions from the frozen copy of the dataset. Freezes should not be part of the main database and should not be used for active research, but archived to enable existing results to be revisited.

There is an ongoing discussion about the nature of desired replicability and reproducibility in various domains. Chris Drummond suggested in [87] a distinction between these two terms, based on whether the focus is on repeating the experimental setup and subsequent findings (replicability) or the results themselves (reproducibility). Cases of dishonesty, incompetence, or error do happen. The prominent examples in recent years include a programming error in the calculation of the impact of debt on economic growth [88] or insufficiently controlled statistics in a study examining the impact of abortion on crime rates [89]. Similarly, the interpretation of the collected massive data may be problematic. Bertrand et al. in [90] examined the sentiment of New York City on the basis of collected Twitter messages. In the following articles in the popular press [91], the authors identified the saddest spot of the city as Hunter College High School. This has proven to be a mistake in the data interpretation, where tweets from a single account in close proximity to the school greatly biased the results. Being able to check and identify such errors is only possible if the underlying data is available. Although it is important to have access to the exact description of the experiment or a study, as well as the collected data or extracted features on which the algorithms can be applied to produce the same results (replicability), it may be argued that, beyond cases of scientific fraud or incompetence, such replication does little to strengthen the results. The value of reproducibility typically arises from deriving the same results from different experimental setups different from each other. Mina Bissell points in [92] to the challenges of replication in a biomedical context, due to the required cost, expertise, sensitivity to conditions etc. We can see how the concern is valid in various domains, including massive data collection efforts, where the cost and time required to collect datasets, although diminishing, may prohibit the exact replication efforts.

We believe that frozen datasets from massive collection studies, allowing for replication to the last decimal place by using the same algorithms, can be a solution for the important issue of transparency of science and ensuring that re-visiting the findings is possible. It is, however, even more significant to be able to reproduce the results in different settings, which by definition will vary, at least slightly, in population, setup, duration etc. In this context, a small fraction of users dropping out of the study and deleting their information from the published dataset should not harm the replicability, as the results should be robust to such small perturbations. There is currently no good answer to the problem of

balancing the privacy of the users — inherent right to decide about data access authorizations — and the availability of the data for the purpose of reproduction of the results and general transparency. The solution will likely require both legal and technical frameworks for making the data available for the purpose of reproduction, but it will require new authorizations for other purposes.

We recommend:

A simple yes/no informed consent option does not live up to the complex privacy implications related to studies of human behavior. For that reason, we believe that users should play a more active role in shaping their involvement in such studies. This view gains support from studies showing that people do not, in general, realize smartphone sensing capabilities nor the consequences of privacy decisions [10, 93, 94].

Additionally, we suggest to carefully consider special cases where the participants may not have the competence or the authority to fully understand the privacy aspects [45, 95–97]. For these reasons we urge special caution in cases where data collection is performed for unspecified later use without clearly stated study purposes, as well as when information about what long-term plans for the data collection is not clearly laid out (e.g. what happens to the data once the study is concluded) [52]. In short, we propose a move towards adapting the principles of Living Informed Consent in studies involving human subjects.

4 Data Security

The security of the collected data, although necessary for ensuring privacy goals, is not often discussed when reporting on collection of large-scale sensor-driven human data [24, 28, 35, 42, 43, 45, 61]. In the next sections we illustrate how security has been addressed in the current, centralized frameworks and how it can be integrated in (future) distributed solutions; what follows is not an exhaustive list, but a compendium of important techniques that can be applied for frameworks for data collection human subjects, as well as potential attacks to consider.

4.1 Common Solutions

The centralized architecture, where the data is collected in the form of a single dataset (typically stored in a single database), has been the preferred solution in the majority of the surveyed projects [20–22, 24, 26, 32, 40, 42, 43, 45, 45–48, 50, 51, 58–60, 96]. When a data package reaches the central server, information is usually stored in SQL databases (e.g. [20, 30, 31, 58, 59]) and aggregated for later analysis.

Centralized architectures suffer from several security problems. Availability is difficult to guarantee when the server becomes overloaded with heavy traffic or subject to a Denial-of-Service attack and, if compromised, a single server can reveal all user data at once.

Malware and viruses for mobile phones are on the rise; given the amount of sensitive information present on the devices, there is a need for mobile applications that take this reality into consideration in order to avoid loss of personal data [16]. To address this problem, some of the frameworks reduce the time the raw sensor information is stored on the device, for example, the *Darwin* platform discards data records once a classification task has been performed. Such approaches, however, are not the norm, most of the sensing applications we surveyed use an opportunistic approach to data uploading, pushing data only when the user is connected to WiFi. As a consequence, devices may end up with large amounts of data stored on the device memory [59], which may introduce a security threat if the devices do not use encrypted file-systems by default. A possible way to tackle this problem is by employing frameworks (such as FunF [20]) that provide reliable data storage systems by encrypting files before moving them

to phone memory by minimizing the amount of data transmitted [42].

Data transmission should be realized over HTTPS (HTTP Secure) to provide protection in the transport layer, such as for example in [28,36,37,61]. We note that some of the surveyed frameworks transmit data over plain HTTP [29,42,43,49,51]. Although this does not automatically indicate security problems, it is a good practice to use transport layer encryption and the protection it offers.

Even encrypted content can disclose information to malicious users, for example when the traffic flow is observed. The opportunistic architecture of transmission and battery constraints does not allow smartphones to mask communication channels with dummy traffic to avoid analysis of the communication patterns (traffic analysis) [29,36].

We recommend:

We note that in all of the surveyed frameworks [28–31,34–37,47,49,61], the mechanisms for access control, user authentication, and data integrity checks (when present), were implemented specifically for the purpose of a given study. While ‘closed’ custom solutions are the norm, they pose an intrinsic problem for privacy due to the complexity of the issue. No single group can be expected to solve every aspect of data security, hence both openness and collaboration are necessary, so that researchers do not have to create new security platforms for every new study.

Finally, we recommend that the security of the entire platform (network and server) is enhanced by adhering to standard checklists, as illustrated in the guidelines on firewalls [98] and intrusion detection systems [99] by the National Institute of Standards and Technology (NIST).

4.2 Distributed Architecture

In recent years, it has been a trend for businesses to store data in highly distributed architectures, or even off-site, in the ‘cloud’. We understand cloud as any remote system which provides a service relying on the use of shared resources [100,101]. An example can be a storage system which allows the users to backup their files and ubiquitously access them via the Internet (e.g. Dropbox) or a service for renting servers and related resources (e.g. Amazon Web Services).

Apart from facilitating the processes of data storage and manipulation, employing cloud solutions could improve the overall security of the collection efforts. As noted above, it is currently typical for platforms to be designed and implemented from scratch, in an environment where thorough testing with respect to security may not be a priority. If server platforms such as Amazon EC2 are used in the data collection frameworks, security mechanisms such as access control, encryption schemes, and authorization can be enforced in standard and well-tested ways. This primarily applies to moderately sensitive data that needs to be accessed in real-time, when keeping it on an offline tightly controlled machine is not feasible.

Using cloud solutions can make it easier to create data collection frameworks that allow users to *own* their personal information. This allows for continuous monitoring of the personal data, controlling the access, and verifying deletion, which in turn may make users more willing to participate in the studies. One possible way to achieve such personal data stores is to upload the data from the mobile devices to personal datasets (e.g. personal home computers, cloud-based virtual machines) as shown in *Vis-a-Vis*, *Confab*, *MyLifeBits* platforms, rather than to a centralized system. On the one hand, with these electronic aliases, users will feel more in control of their personal data, diminishing their concerns about systems that centralize data. On the other hand, part of the security of users’ own data will inevitably rely on the users themselves – and on the service providers who manage the data.

Given the sensitive nature of the data, vulnerabilities in the cloud architectures can pose serious risks for the studies and, while cloud solutions might provide an increased level of security, they are definitely

not immune to attacks (see [102] for attacks taxonomy and [103] for a general analysis on the cloud security issues).

Sharing resources is a blessing and a curse of cloud computing; it helps to maximize the utility/profit of resources (CPU, memory, bandwidth, physical hardware, etc.), but at the same time it makes it more difficult to assure security, as both physical and virtual boundaries have to be reinforced. The security of the Virtual Machines (VMs) becomes as important as the physical security because “any flaw in either one may affect the other” [103]. Since multiple virtual machines are hosted on the same physical server, attackers might try to steal information from one VM to another using cross-VM attacks [104]. One way to violate the data confidentiality is to compromise the software responsible for coordinating and monitoring different virtual machines (hypervisor) by replacing its functionalities with others aimed at breaching the isolation of any given pair of VMs, a so-called Virtual Machine Based Rootkit [105].

Another subtle method to violate security is via side-channels attacks [106]. These exploit unintended information leakage due to the sharing of physical resources (such as CPU duty cycles, power consumption, memory allocation). For example, a malicious software in one VM can try to understand patterns in memory allocation of another co-hosted VM without the need of compromising the hypervisor. One of the first real examples of such attacks has been shown in [107], where the researchers demonstrated how to extract private keys from an adjacent VM.

Finally, deleted data in one VM can be resurrected from another VM sharing the same storage device in a Data Scavenging attack [103] or the whole cloud infrastructure can be mapped to locate a particular target VM to be attacked later [104]. In addition, the volatile nature of the cloud resources makes it difficult to detect and investigate attacks. When VMs are turned off, their resources (CPU, RAM, storage, etc.) become available to other VMs in the cloud [100], making it difficult to track processes and gather forensic evidence.

We recommend:

While we believe that the cloud is the future of massive data collection studies, the current situation still presents some technical difficulties that need to be addressed. For this reason, in section 6.2 we recommend focus on methods to control data treatment (*information flow and data expiration*) for remote storage systems in order to ensure user compliance with privacy agreements. For the time being, data security can be improved by combining some of the solutions previously outlined. For example, information should be stored encrypted when still on the smartphones and then transported to the servers via secure channels (HTTPS). After processing on researcher machines, they can be re-encrypted prior to cloud storage.

5 Privacy and Datasets

The datasets created in massive data collection studies often contain very sensitive information about the participants. A common definition of Personally Identifiable Information (PII) is ‘any information about an individual maintained by an agency, including any information that can be used to distinguish or trace an individual’s identity, such as name, social security number, date and place of birth, mother’s maiden name, or biometric records; and any other information that is linked or linkable to an individual, such as medical, educational, financial, and employment information¹. It is researchers’ responsibility to protect users’ PIIs, and consequently their privacy when disclosing the data to public scrutiny [12–14] and to guarantee that the services provided will not be malicious [32, 49, 108]. PIIs can be removed, hidden in group statistics, or modified to become less obvious and recognizable to others, but the definition of PII is context-dependent, sometimes making it very difficult to select which information needs to be purged. In

¹NIST Special Publication 800-122 <http://csrc.nist.gov/publications/nistpubs/800-122/sp800-122.pdf>

addition, modern algorithms can re-identify individuals, even if no apparent PII is published [15, 16, 109–111]. Attempts to provide anonymity often decrease the data utility by reducing resolution or introducing noise, resulting in privacy-utility trade-off [112].

5.1 Privacy Implementations

When sensitive information is shared with untrusted parties, technical mechanisms can be employed to enhance the privacy of participants by transforming the original data. We present two common ways to augment users' privacy: noise and anonymization, and discuss developments in applied homomorphic encryption. For a classification of different privacy implementation scenarios—such as multiple, sequential, continuous, or collaborative data publishing—see [113].

5.1.1 Noise

A difficult trade-off for researchers is how to provide third parties with accurate statistics on the collected data while protecting the privacy of the individuals in the records: how to address the problem of *statistical disclosure control*. Although there is a large literature on the topic, the variety of techniques can be coarsely divided into two families: approaches that introduce noise directly in the database (*data perturbation models* or *offline methods*) and a second group, that interactively modifies the database queries (*online methods*).

Early examples of the privacy-aware data-mining aggregations can be found in [114], where the authors considered building a decision-tree classifier from training data with perturbed values of the individual records, and showed that it is possible to estimate the distribution of the original data values. This implies that it is possible to build classifiers whose accuracy is comparable to the accuracy of classifiers trained on the original data. In [115] the authors showed an Expectation Maximization (EM) algorithm for distribution reconstruction, providing robust estimates of the original distribution given that a large amount of data is available. A different approach was taken in [116], where the authors presented a new formulation of privacy breaches and proposed a methodology for limiting them. The method, dubbed *amplification*, makes it possible to guarantee limits on privacy breaches without any knowledge of the distribution of the original data. An interesting work on the trade-off between privacy and usability of the perturbed (noisy) statistical databases has been included in [117]. These results were extended in [118], where the authors investigated the possibility of a sublinear number of queries on the database which would guarantee privacy, and thus extend the framework. A second work consolidated discoveries from [117], demonstrating the possibility to create a statistical database in which a trusted administrator introduces noise to the query responses with the goal of maintaining privacy of individual database entries. In [119] the authors showed that this can be achieved using a surprisingly small amount of noise — much less than the sampling error — as long as the total number of queries is sublinear in the number of database rows.

A different approach was evaluated by Dwork et al. in [120], where an efficient distributed protocol for generating shares of random noise and securing against malicious participants was described. The innovation of this method was the distributed implementation of the privacy-preserving statistical database with noise generation. In these databases, privacy is obtained by perturbing the true answer to a database query by the addition of a small amount of Gaussian or exponentially distributed random noise, effectively eliminating the need for a trusted database administrator. Finally, in [121] Chawla and Dwork proposed a definition of privacy (and privacy compromise) for statistical databases, together with a method for describing and comparing the privacy offered by specific sanitization techniques. They obtained several privacy results using two different sanitization techniques, and then showed how to combine them via cross training. This work was advanced in a more recent study [122], where the scope of the techniques was extended to a broad class of distributions and randomization by a histogram construction

to preserve spatial characteristics of the data, allowing approximation of various quantities of interest in a privacy-preserving fashion, e.g. cost of the minimum spanning tree on the data.

5.1.2 Anonymization

The most common practice in the data anonymization field is to one-way hash all the PII's such as names, MAC addresses, phone numbers, etc. This breaks the direct link between the user in the given dataset and other, possibly public datasets (e.g. Facebook profile). The raw data can be uploaded from the smartphone to an intermediate proxy server, where the hashing is performed. This technique is used in the *LDCC* study. Once anonymized, the data can be transferred to a second server to which researchers have access. A more privacy-preserving option is to hash the data directly on the smartphones and then upload the results onto the server for analysis; a solution used in many of the MIT studies [20, 21, 58, 59] and in the *Copenhagen Networks Study* [123]. In principle, hashing does not reduce the quality of the data (provided that it is consistent within the dataset), but it makes it easier to control which data are collected about the user and where they come from. It may, however, reduce the utility if the labels themselves are to be analyzed (e.g. mining the area codes of phone numbers). In this case the mining should happen before hashing, and hashes should be stored together with low-dimensional results computed from the raw data. Some types of raw data – such as audio samples – can be *obfuscated* directly on the phone without losing the usability before being uploaded [26, 60]. Hashing PII's does not guarantee that users cannot be identified in the dataset [12–14]. Section 5.2 contains examples of methods that revert and break such ‘anonymity’ through the use of auxiliary (non-hashed) information, de facto revealing individuals’ identities.

A frequent method employed for anonymization is ensuring k -anonymity [38] for a published database. This technique ensures it is not possible to distinguish a particular user from at least $k - 1$ people in the same dataset. *AnonySense* and the platform developed for the *LDCC* both create k -anonymous different-sized tiles to preserve users’ location privacy, outputting a geographic region containing at least $k - 1$ people instead of a single user’s location. Nevertheless, later studies have shown how this property is not well suited for a privacy metric [124]. Machanavajjhala et al. tried to solve the k -anonymity weaknesses with a different privacy notion called l -diversity [125]. This was extended by Li et al. by proposing a third metric, t -closeness [126].

While today’s anonymization techniques might be considered robust enough in providing privacy to the users [127], our survey contains methods that manage to re-identify participants in anonymized datasets (see section 5.2).

5.1.3 Homomorphic Encryption

Homomorphic encryption is a cryptographic technique enabling computation with encrypted data: operations in the encrypted domain correspond to meaningful operations in the plaintext domain [33, 128]. This means users can allow other parties to perform operations on their encrypted data without exposing the original plaintext, thereby limiting the sensitive data leakage.

This technique can find application in health-related studies, where patients’ data should remain anonymous before, during, and after the studies, with only authorized personnel having access to the clinical data. *Data holders* (hospitals) can send encrypted information on behalf of *data producers* (patient) to untrusted entities (e.g. researchers and insurance companies), who process them without revealing the data content, as formalized by *mHealth*, an early conceptual framework. *HICCUPS* is a concrete prototype that allows researchers to submit medical requests to a query aggregator that routes them to the respective caregivers. The caregivers compute the requested operations using sensitive patients’ data and send the reply to the aggregator in encrypted form. The aggregator then combines all the answers and delivers the aggregate statistics to the researchers. A different use of homomorphic encryption to preserve users’ privacy is demonstrated by *VPriv*. In this framework the central server first collects anonymous

tickets produced when cars exit the highways, then, by homomorphic transformations, it computes the total amount that each driver has to pay at the end of the month.

Secure two-party computation can be achieved with homomorphic encryption when both parties want to protect their secrets during the computations: none of the involved entities needs to disclose its own data to the other, at the same time they achieve the desired result. In [129] the researchers applied this technique to private genome analysis. A health care provider holds a patient's secret genomic data, while a bioengineering company has a secret software that can identify possible mutations. Both want to achieve a common goal (analyze the genes and identify the correct treatment) without revealing their respective secrets: the health care provider is not allowed to disclose patient's genomic data; the company wants to keep formulas secret for business reasons.

Recently, much effort has been made in building more efficient homomorphic cryptosystems (e.g. [130, 131]). It is still hard to foresee whether or when the results will be practical for massive data collection frameworks.

5.2 Attacks against Privacy

While researchers mine the data for scientific reasons, malicious users can misuse it in order to perpetrate 'illegitimate acquisition and analysis of people's information' [16].

Like scientists, reality thieves aim to decode human behavior such as everyday life patterns [124], friendship relations [2, 48], political opinions [59], or purchasing profiles². Businesses invest in data mining algorithms in order to make high-quality predictions of customer purchases, while others are interested in analyzing competitors' customer profiles [9].

Privacy scandals such as *Netflix Prize*, *AOL searcher* [14], and the *Governors of Massachusetts health records* [13] show that the de-identification of data elements is often insufficient, as it may be reversed, revealing the original individuals' identities.

A common approach to data re-identification is to compare 'anonymized' datasets against the publicly available ones; such schemes are called *side-channel information* or *auxiliary data* attacks. For such attacks, online social networks are excellent sources of auxiliary data [110]. In recent studies [132, 133], researchers have shown that users in anonymized datasets may be re-identified studying their interpersonal connections on public websites such as Facebook, LinkedIn, Twitter, Foursquare, and others. Researchers identified similar patterns connecting a pseudonym in the anonymized dataset to the user's real identity in a public dataset. It is difficult to thwart such side-channel attacks, as even a small number of low-resolution datapoints from the dataset can be used to uniquely fingerprint a user as shown in [15], and obtaining a similar small number of datapoints about an individual from public sources may be equally easy. Using examples from the studies we have surveyed, users' anonymity might be compromised in *VPriv* and *CarTel* every time only a single car is on a highway, because it is possible to link the anonymous packets reaching the server to that (unique) car. The same type of consideration is valid for *AnonySense* and *VirtualWalls*; if only one user is performing the sensing task (first platform) or if only one user is located inside a room at a certain time (second platform). *CenceMe*, *FollowMe*, and *Locaccino* allow the users to update their daily habits. Studying symmetries (e.g. in commuting) and frequencies (e.g. meals or weekly workouts) of these behaviors, it is possible to discover underlying patterns and perpetrate attacks against users' privacy [110]. More generally, it is often the case the data released by researches is not the source of privacy issues, but the unexpected inferences that can be drawn from it [134].

Internal linking [110] is another approach that aims to connect different interactions of one user within the same system. For example, in [37] two reports uploaded by a single user might be linked on the basis of their timing.

Data collected by seemingly innocuous sensors can be exploited to infer physiological and psychological states, addictions (illicit drugs, smoking, drinking), and other private behaviors. Time and temperature

²<http://adage.com/article/digital/facebook-partner-acxiom-epsilon-match-store-purchases-user-profiles/239967/>

can be correlated to decrease location privacy [135], while accelerometers and gyroscopes can be used to track geographic position [109] or even to infer peoples' mood [110]. A recent study showed that accurate estimates of personal attributes (such as IQ levels, political views, substance use, etc.) can be inferred from the Facebook Likes, which are publicly available by default [136].

These threats are exacerbated because the general public is often unaware of what can be inferred from seemingly harmless data [51] and of smartphone sensing capabilities [93]. For example, participants of the *Bluemusic* experiment did not show any concerns related to options such as 'recording all day, everyday' and 'store indefinitely on their mobile phone' related to data collected by accelerometers because this sensor is perceived as 'not particularly sensitive' [51].

While protecting the privacy of an individual user is difficult, data with a network structure make it even more challenging. The nodes can be identified on the basis of the network structure and knowledge of some attributes of the neighbors of the node [137]. Even when using conventional de-identification techniques, the information embedded in the network structure can be sufficient to find the identity of the user. Anonymization of network data to prevent these attacks is difficult, and requires careful changes in the disclosed network structure to reduce the possibility of re-identification while keeping the utility of the network data. Cheng et al. showed in [138] that k -isomorphism, anonymization based on formation of k pairwise isomorphic subgraphs is both sufficient and necessary to protect against re-identification. The problem of constructing the subgraphs is, however, NP-hard and such operation can significantly reduce the utility of the network data.

Protecting against re-identification in the network is only part of the solution; perhaps even more important is protection against attribute disclosure. The latter happens when certain attributes the user would like to keep private are disclosed due to the user's position in the network. Davis et al. in [139] recovered the location of untagged tweets using the network structure of the followers and their geo-tagged tweets. In a dataset related to a particular topic on Twitter, they showed an increase of 45% in the number of messages that could be located. Sensitive attribute inference was also showed in [140], where the authors mixed private and public profiles in social networks, using publicly available friendship structure and group memberships to recover hidden values of the user, such as gender, religion, and origin. Using models of variable complexity and network properties such as autocorrelation, caused by homophily or influence, they were able to successfully show significant leakage of information from friendships and groups users join. Chester and Srivastava introduced in [141] an approach to anonymize labeled social networks. Called α -nearness, it produces label distribution in every neighborhood of the graph close (within α) to that of the entire network by producing a graph with an augmented set of edges.

Privacy in network data is arguably the hardest challenge of the entire domain. It touches the legal and ethical dimensions (who owns the story about me), informed consent (how my assent influences others), and data control (even if my data is deleted, it may still be recovered from other users). Addressing the issue in full is beyond the scope of this article. We recommend that these problems need to be considered in addition to the privacy of a single user, which is a necessary first step.

The consequences of loss of sensitive information can be long lasting; it is almost impossible to change personal relationships or life patterns³ after an *identity theft attack* or to avoid other types of criminal activity (stalking) that might occur because of misuses of behavioral datasets [16].

³Although for slightly different reasons, in 2010 Google's Executive Chairman Eric Schmidt suggested automatic changes of virtual identities to reduce the limitless power of the 'database of ruin' <http://online.wsj.com/article/SB10001424052748704901104575423294099527212.html>.

We recommend:

We suggest that the potential for misuse and attacks should be mentioned in the informed consent processes. Finally, many existing platforms build privacy for the users on the hypothesis that techniques like k -anonymity and protections against traffic analysis or side channels will possibly be added in future, but at the time of writing, such techniques have not yet been integrated in any study. As practitioners of massive data collection, we feel that one of the most important challenges of future studies will be to build common frameworks that provide holistic, reusable solutions addressing privacy concerns.

6 Information Ownership and Disclosure

An attractive solution to some of the issues listed previously would be frameworks that can guarantee the users ways to control at any time who is in possession of their data and for what reason, but past attempts at creating such digital rights management (DRM) systems for privacy purposes did not produce the expected results. Further, without trusted computing bases there is no practical way of enforcing that data are not to be retained/copied or forwarded to third parties [29, 142].

One problem remains in the issue of whether the users allow researchers to physically own the data stored on the universities' servers (see section 4.1) or simply allow researchers to use the information stored as personal datasets (section 4.2 and 6.1). Users must trust researchers and service providers to properly manage their personal information as agreed and not to expose any sensitive data to unauthorized parties. In the following sections we provide further details about two main information disclosure scenarios: the explicit and conscious process of distributing information to other parties, and techniques to control data disclosure, such as information flow control and data expiration systems.

6.1 Sharing

Individuals' notions of information sensitivity, and therefore sharing patterns, vary [49, 50, 77, 78]. Some information, however, should always be perceived as sensitive and requires special attention. Examples include health-related, financial, or location data. The sensitivity of information is often proportional to its research value, making users reluctant to share such data [93, 109, 143]. For example, recent studies have demonstrated that social networks can be mined in order to discover psychological states [110, 111], which can be later used to detect unusual patterns and prevent or treat psychological disorders (social anxiety, feelings of solitude, etc.).

6.1.1 Sharing with other users

Social networks and smartphone applications such as *CenceMe*, *Bluemusic*, *FollowMe*, and *Cityware* show people are comfortable with the idea of sharing personal information with friends [11]. However, in many cases the data sharing options lack granularity. For example, users of *CenceMe* and *FollowMe* can unfriend other participants and thus resize the sharing set, while users of *Cityware* or *GreenGPS* need to switch off the Bluetooth/GPS device to avoid being tracked. More fine-grained systems exist, in which the users can visualize and edit boundaries and resolution of the collected information before sharing it with others [26, 29, 40, 50].

Location sharing, in particular, is a multifaceted topic. Today, users can instantaneously share their location through an increasing number of services: using native applications (Foursquare, Google+), by means of social network websites (Facebook, Twitter) and within social experiments [42, 47, 49, 50, 78]. The attitude of users towards location sharing varies. It has been established the users' understanding

of policies and risks is quite limited and often self-contradictory [28, 50, 78, 144]; although the majority of users seem to be at ease in sharing their check-ins, they assert to be worried about the ‘Big-Brother effect’ when asked directly [67, 94, 109]. These contradictions and the natural complexity of different preferences in location sharing policies raise challenges for researchers.

We recommend:

We find that better ways to inform users about possible dangers related to sharing data are needed (see section 3 and 5). In addition, we believe new dynamic platforms should be created to enable users to visualize and control their information flows. One example would be a platform showing how to discern which areas can report users’ location and which cannot [50].

6.1.2 Sharing with researchers

As discussed above, the most common approach for the studies surveyed here is to collect user-data in centralized servers. This means that when the data leaves the smartphone, the user effectively loses control over them and cannot be sure, from the technical perspective, that her privacy will be respected. The opposite approach is to let the users own the data so they can control, access, and remove them from databases at any moment, as noted in section 4. A possible way to achieve this is to upload the data from the mobile devices not to a single server, but to personal data stores (e.g.: personal home computers, cloud-based virtual machines) as shown in the architectures in [28–30]. It is then possible to deploy distributed algorithms capable of running with inputs coming from these nodes, as illustrated by the *Darwin* framework.

While the advantages of cloud computing for the data collection frameworks are numerous (as discussed in section 4.2), this architecture is not immune from privacy concerns for users and technical barriers for scientists. The former are worried about the confidentiality of their remote information, the latter need practical ways to collect and perform analysis on the data.

6.2 Data Control

Controlling ownership of digital data is difficult. Whenever images are uploaded to photo-sharing services, or posts are published on social networks, the user loses direct control over the shared data. While legally bound by usage agreements and terms of service, service providers are out of user’s direct control. The open problems in data disclosure include time retention and information flow tracking. Today’s frameworks try to solve these issues by legal means, such as declarations asserting that ‘any personal data relating to the participants will not be forwarded to third parties and will be destroyed at the end of the project’ [24]. In this chapter we discuss the state-of-the-art of the technical means to limit information disclosures and possibilities of integration with research frameworks.

6.2.1 Information Flow Control

Information Flow (IF) is any transfer of information from one entity to another. Not all the *flows* are equally desirable, e.g. a sheet from a CIA top-secret folder should not leak to another file of lower clearance (a public website page, for instance). There are several ways of protecting against information leaks. In computer science, Access Control (AC) is the collection of network and system mechanisms that enforce policies to actively control how the data is accessed, by whom, how, and who is accounted for.

Some attempts at building decentralized information flow control (DIFC) systems to track information flows in distributed environments are *JIF* extensions (such as *Jif/Split* [145] and *CIF* [146]) or *HiStar* extensions like *DStart* [147], which utilize special entities at the endpoint of each machine to enforce information exchange control.

An interesting approach taken by *Neon* [148] can control, not only information containers (such as files), but also the data written inside the files. It is able to track information flows involved in everyday data manipulations, such as cut and paste from one file to another or file compression. In these cases, privacy policies about participants' records stored in datasets cannot be laundered on purpose or by mistake. *Neon* applies policies at the *byte-level*, so whenever a file is accessed, the policy propagates across the network, to and from storage, maintaining the binding between the original file and derived data to which the policy is automatically extended.

Privacy Judge [149] is a browser add-on for online social networks to control access to personal information published online which uses encryption to restrict who should be able to access it. Contents are stored on cloud servers in encrypted form and place-holders are positioned in specific parts in the OSN layouts. The plug-in automatically decrypts and embeds the information only if the viewer has been granted access. The domains of *Privacy Judge* can be extended by similar tools to limit access and disclosure of personal datasets: the participant could remove one subset of his entries from one dataset, affecting all the studies at once.

The complementary approach to the above systems is to ensure control of information disclosure *a-posteriori*. This means that whoever is in possession of the data, or processing them, can be supervised by the users, and therefore each misuse or unwanted disclosure can be detected.

Such auditing systems include *SilverLine* [150], a tracking system for cloud architectures that aims to improve data isolation and track data leaks. It can detect if a dataset collected for one experiment is leaked to another co-resident cloud tenant. Therefore, users can directly control where their personal information is stored and who has access to it.

CloudFence [151] is another data flow tracking framework in which users can define allowed data flow paths and audit the data treatment monitoring the propagation of sensitive information. This system – which monitors data storage and service providers (any entity processing the stored data) – allows the user to spot deviations from the expected data treatment policies and alert them in the event of privacy breaches, inadvertent leaks, or unauthorized access.

For maintenance reasons (backups, virus scanning, troubleshooting, etc.), cloud administrators often need privileges to execute arbitrary commands on the virtual machines. This creates the possibility to modify policies and disclose sensitive information. To solve this inconvenience, *H-one* [152] creates special logs to record all information flows from the administrator environment to the virtual machines, thereby allowing the users to audit privileged actions.

Monitoring systems like *Silverline*, *CloudFence*, and *H-one* can be deployed for research frameworks to give the users a high degree of confidence in the management of their remote personal information stored and accessed by cloud systems.

We recommend:

Unfortunately, these solutions are still not easily deployable since a) many of them require Trusted Computing Bases [28, 153, 154] (to prove trusted hardware, software, and communications) which are not common at the time of writing; b) some require client extensions that reduce usability and might introduce new flaws [149]; and c) covert channel attacks are not defeated by any IF techniques (e.g. screenshots of sensitive data). In addition, enforcing information flow policies also needs to take into account incidental (and intentional) human malpractices that can launder the restrictions. We note that none of the surveyed frameworks provided information flow controls, and only few of them mentioned auditing schemes.

While this type of user-protection is less deployable than others, we believe that auditing will have a place in future massive data collection backends. We also hold that a paradigm shift in data treatment where users will *own* their personal sensitive information, will make such auditing systems more feasible.

6.2.2 Data Expiration

As we have recently seen for Google Street View and Facebook, service providers are very reluctant to get rid of collected data⁴. After user deletion requests, service providers prefer to make the data inaccessible – hidden from view, behind a disabled profile – rather than physically purging the data from storage. To aggravate this situation, data is often cached or archived in multiple backup copies to ensure system reliability. Therefore, from the users' perspective it is difficult to be completely certain that every bit of personal information has been deleted. Consequences of unlimited data retention can be potentially catastrophic: if private data is perpetually available, then the threat to user privacy becomes permanent [155]. A solution to this problem is *retroactive privacy*: meaning that data will remain accessible until – and no longer than – a specified time-out.

Here we illustrate some of the most interesting approaches to address the data expiration strategy, narrowing our focus to systems that can be integrated with research frameworks. The criteria in the selection are a) user control and b) ease of integration with existing cloud storage systems. Self-destructing data systems prefer to alter data availability instead of its existence, securing data expiration by making the information unreadable after some time. The concepts 'self-destructing data' and 'assured data deletion' were first presented in [156]. Data is encrypted with a secret key and stored somewhere to be accessible to authorized entities. Then, after the specified time has passed, the corresponding decryption key is deleted, making it impossible to obtain meaningful data back. This is a trusted-user approach and relies on the assumption that users do not leak the information through side channels, e.g. copying protected data into a new non-expiring file. Therefore, these systems are not meant to provide protection against disclosure during data lifetime (before expiration), as DRM systems are designed to achieve⁵. Self-expiring data systems can be integrated in research frameworks to enhance privacy in sharing data, permitting the participants to create personal-expiring data to share with researchers for only a pre-defined period of time.

Key management—which is the main concern in such systems—can be realized either as a centralized *trusted* entity holding the keys for all the users, or keys can be stored across different nodes in a distributed network where no trusted entity is employed.

Ephemerizer [157, 158] extends the principles outlined in [156] to interconnected computers implementing a central server to store the keys with respective time-outs. The server periodically checks the keys for their time-out and delivers them only if their time has not yet expired. An approach that avoids the necessity for a trusted party is *Vanish* [159], a distributed solution that spreads the decryption key bits among different hosts: after the usual encryption phase (key creation, file encryption and storing), the key is split into secret shares and distributed across random hosts in a large distributed hash table (DHT) (DHT are decentralized systems that store $\langle \textit{key}, \textit{value} \rangle$ mappings among different nodes in a distributed network). The key tells which node is holding the corresponding value/piece of data, allowing value retrieval, given a key. According to the secret sharing method [160], the recovery of k (threshold) shares on n total shares permits the reconstruction of the original key and therefore the decryption. What makes the data expire/vanish is the natural turnover (churn) of DHTs (e.g.: Vuze) where nodes are continuously leaving the network making the pieces of a split key disappear after a certain time. When there are not enough key shares available in the network, the encrypted data and all its copies become permanently unreadable. There are two main limits on the Vanish system. First, the requirement for a plug-in that manages the keys reduces its usability. Secondly, the time resolution for expiration is limited to the natural churn rate of the underlying DHT and it is expensive to extend due to re-encryption and key distribution.

As pointed out in [161], the idea of turning the nodes' instability into a vantage point for data

⁴https://www.schneier.com/blog/archives/2009/09/file_deletion.html,
<http://www.dailymail.co.uk/sciencetech/article-2179875/Google-admits-STILL-data-Street-View-cars-stole.html>

⁵DRMs assume user untrustworthiness limiting the use and/or disclosure of a digital content in all its possible forms e.g.: duplication and sharing.

expiration might introduce serious problems. Attacker can crawl the network and harvest as many stored values as possible from the online nodes before they leave the network. Once enough raw material has been collected, the attack can rebuild the decryption key, resuscitating the data.

Based on the same cache-ageing model of Vanish, but immune to that attack, is *EphPub* [155], in which the key distribution mechanism relies on the Domain Name System (DNS) caching mechanism. The key bits are distributed to random DNS resolvers on the Internet, which maintain the information in their caches for the specified *Time To Live*. This solution is transparent to users and applications, not involving additional infrastructure (a DHT or trusted servers) nor extra software (DHT client).

Another solution for data expiration is *FADE* [162], a policy access control system that permits users to specify read/write permissions of authorized users and applications other than data lifetime. The underlying idea is to decouple the encrypted data from the keys: information can be stored in untrusted cloud storage providers and a *quorum of distributed key managers* guarantees distributed access control permissions for the established period of time.

Given data redundancy and dispersion, it is almost impossible to ensure full control over distributed data, especially when users are directly involved, as it cannot be prevented that human users manually write down the information, memorize it, or take a picture of the screen and share it in a non-secure manner [149]. While everlasting data is generally dangerous in any context, the problem becomes even more important for studies where the amount and the sensitivity of the collected data can be substantial. On the other hand, we can expect that even high-resolution data of a certain kind, for example mobility traces, will become less sensitive with the passage of the time. As a society, we will need to understand how to deal with massive amounts of high-resolution data existing after their owners have passed away.

We recommend:

The systems described above can be part of privacy-aware research frameworks that can automatically take care of purging old information from the database. Providing users with ways to control sharing schemes and information lifetime might attract more participants, who may be currently be reluctant to share their personal data. We would like to emphasize that the mentioned solutions do not provide complete data protection and have been inspected by the scientific community for only a brief period of time. It is not current practice in the examined frameworks to include the data retention procedures and lifetimes in the user agreements or informed consent. While it is still uncertain whether assured deletion and data expiration are technically secure, we note that there are limits beyond which only legal means can guarantee the users the conformity to certain procedures in data management and retention. The data deletion schemes must, however, allow for studies' replicability; the minimal set of data or preferably features required to replicate published results must be retained.

6.2.3 Watermarking

Digital watermarking is a process of embedding a marker in the data for the purposes of content tracking, authentication, or owner identification, among others. Embedding the marker aims to preserve the utility of the data for a particular purpose, assuming a certain level of fault-tolerance in the data in a given context. The general requirements of watermarking include that it should be 1) imperceptible, not introducing any perceptible artifacts into the data 2) robust, being immune to certain classes of transformations, 3) blind, in that the detections should neither require knowledge of the watermark or the original database, and 4) incrementally updatable [163].

Transactional watermarking, also known as fingerprinting, is a technique of placing different marks in different copies of the data. This allows the data owner to trace copies of the data and identify the leaks [164]. The attackers are, in our context, researchers and other entities who have either been granted access to the data, but share or use them in an unauthorized way, or have obtained the data

from unauthorized sources. In active attacks, the entity attempts to remove the watermark or to make it undetectable [165]. A special case of active attacks is a collusion attack, in which the attacker combines several copies of the data, each with a different watermark, to construct a watermark-free copy. Resistance to these attacks is critical for fingerprinting, if there is a possibility that the attacker can gain access to multiple copies of the same data. This can happen when one entity can request multiple copies of the data, each with a different embedded watermark, or when several entities can collaborate with each other, sharing their datasets. Whether it is a concern, depends on the data access framework, how the data is accessed and by whom. If the access is tightly controlled and audited, or the watermark is consistent per entity accessing the data, collusion attack may not be feasible for a single entity. The parties accessing the data may also be unlikely to conspire to produce a watermark-free copy, for example respected researchers or large companies. However, if data access is possible, for example, for anonymous users on the Internet, they may be interested in working together to attack the fingerprint.

Various generic techniques of watermarking relational databases have been developed. Agrawal et al. showed in [163] how a relational database can be watermarked using certain bit positions of some of the attributes of the tuples. These locations and values are determined on the basis of a secret key, chosen by the owner of the data, allowing detection of the watermark with high probability. With enough redundancy in the watermark, it is robust with respect to common database operations, including insertions, updates, and deletions. Guo et al. improved algorithm to watermark numeric attributes in relational databases in [166]. They used groups of tuples representing each bit of the watermark, and by being able to identify which group the tuples belong to, achieved a totally blind system, where only the length of the watermark is needed to recover the watermark. An example of using fingerprints in large datasets is the American Dataset Program (ADT), designed to produce decoy records for the purpose of fingerprinting identity datasets [167]. These decoy entries, created to look realistic and not bias the statistics calculated on the data, can be generated uniquely for every copy of the dataset released. The records are highly unique and are based on a key chosen by the owner of the data, thus they can always be identified.

Watermarking can be a suitable technique for data control in massive data collection efforts. Depending on the nature of the data and expected misuses, the effectiveness may vary, however. We can expect that the problem is often not leaking of the entire dataset, but rather using the data in an unauthorized way. In such a scenario, when the actual data is never leaked, but covertly used against the users, identifying the source of the data leak may be hard, even with the watermark embedded. Some interesting solutions can be envisioned in such cases, for example, if the danger is about abusing collected email addresses of the participants for the purpose of spamming, one can embed the decoy records as described in [167] and monitor the generated email addresses for spam. As long as the watermark does not significantly reduce the utility of the data, embedding it is a good idea. The usefulness may, however, vary in the massive data context.

6.2.4 Contract Governance

All technical means employed for ensuring control of data sharing have their limitations. No system is perfectly secure, covert attacks can always be found, and trying to stop these attacks with only technical means is not feasible; users can be identified, watermarks removed, and data shared beyond controlled systems. In the end, it is the credible threat of legal and business consequences that has to assist in discouraging widespread abuse.

Data access and sharing can be governed by contract agreement, specifying what can and cannot be done with the data, as well as consequences of the abuses. It is common practice for researchers to work under agreements that define allowed uses of the massive data [24, 26]. In the Data For Development (D4D) challenge, researchers accessed the data published by telecommunication operator Orange for the purpose of generating novel insights for the public good. Beyond the technical means of de-identification of the dataset [168], researchers agreed to terms and conditions, stating that they would not attempt the

re-identification of users, share the data with third parties, or otherwise abuse the access [169].

Legal means are routinely employed when granting researchers access to data collected by governmental institutions in registers, such as economic data, personal health records, or education records. In the Netherlands, a contract is signed by the researcher working with the data, while the statement of secrecy is signed by both the researchers and the employing institution [170]. In Denmark, access to registers, where data from the population are grouped and records are identified by civil registration number, is regulated by the Act on Processing of Personal Data which states that personal data applied for statistical purposes may be disclosed and reused with the permission of the Data Protection Agency [171]. Under this Act, a public authority may impose a duty of non-disclosure on the researchers and even de-identified data must be treated as confidential. Breaches are punishable by detention or imprisonment. Similar measures are implemented in Sweden and other Nordic countries [172], with some minor differences in what data exactly can be accessed; for example, in Finland it is not generally possible to access data with personally identifiable information. The guiding principle in all the countries is that the access to data for research purposes must not put the subjects in danger, including the possibility of re-identification. Individuals are entitled to be protected from intrusion, at the same time balance must be found with the legitimate needs of society to access data for the public good.

Legal means are sensitive to geography. For example in Denmark only Danish research environments can be granted access to register data, as it not feasible to effectively enforce contracts abroad [171]. Except for the legal means, no scrambling, grouping, or other statistical randomization techniques are applied to these data. When accessing register data, it is often a practice to require researchers to physically work on the premises of the managing agency, use designated servers for computation, or use authorized and secure connection [170–172]. The data flows are tightly controlled in this context, all performed computations and transfers are logged and audited, and the policy to which researchers agreed is enforced.

In Europe, Council Regulation (EC) No 322/97 of 17 February 1997 on Community Statistics states that the data used for the production of statistics should be considered confidential when they allow for identification of the statistical units, disclosing individual information either directly or indirectly [173]. All the means that can be reasonably used by a third party for such identification have to be considered when deciding whether a statistical unit is identifiable. This goes beyond protection of PIs that directly identify users, including any combination of data that makes identification feasible. Directive 95/46/EC of the European Parliament and of the Council of 24 October 1995 mentions the protection of individuals with regard to the processing of personal data and the free movement of such data (the Data Protection Directive) [174]. The Directive applies to electronic personal data and structured manual files, and it talks about processing, which includes collection, storing, merging, changing, sharing, deleting, etc. The Directive covers fundamental requirements for data processing, including fairness and lawfulness, explicit purpose of collection and analysis compatible with the purpose, and keeping the data identifiable for only as long as it is required. The adoption of the General Data Protection Regulation, superseding the Data Protection Directive and addressing issues such as cloud computing and data generated by online social networks, is expected for 2014, with a following 2-year transition period (http://ec.europa.eu/justice/data-protection/index_en.htm).

In Australia, controls on research data are most commonly imposed by government, as a very high proportion of funding is provided by the Commonwealth, State, and Territory governments [175]. All the aforementioned principles for treatment research data apply in Australia, including requirements for informed consent, removal of identifiable information, and usage only for purposes compatible with the original purpose of data collection. We mention Australia, because Fitzgerald et al. note in [175] how some research expressed frustration with the limitations imposed by the existing legislation. Quoting Dr. Richie Gun of the Department of Public Health, University of Adelaide:

In Australia we are now in a uniquely advantageous position to carry out such [cancer] re-search, as we have mandatory registration of cancers in every State and Territory. We there-

fore have almost complete enumeration of all invasive cancers occurring in Australia, with the potential to carry out epidemiological studies on cancer incidence equal to or better than anywhere else in the world. Unfortunately privacy laws are impeding access to cancer registry data, so that it is becoming increasingly hard to carry out the linkage of cancer registrations with exposure data.

Rulings such as this suggest that we researchers are not to be trusted to protect privacy; that names will be released to outside parties; or that publications will identify individuals. This might be justified if there were some evidence that researchers have actually misused such data. Yet where is such evidence? The fact that there is no evidence of misuse is easily explained: researchers have nothing to gain by providing information and everything to lose. I know that if it became known that confidential information had been given out from my research team, it would be the end of my research and my career.

This statement shows that legal and business means of ensuring proper data flows can be effective in a research context. When researchers have everything to lose and little to gain from abusing the data, they could be entrusted with high-quality data, even including personally identifiable information, just based on their agreement to not abuse this access.

The IPUMS-International is a global initiative led by the University of Minnesota Population Center to coordinate access to high-resolution census data to researchers [176]. The projects within the initiative are only undertaken in countries with an explicit understanding between the official statistical institute and the University of Minnesota [177]. The agreement includes rights of ownership, rights of use, conditions of access, restrictions of use, the protection of confidentiality, security of data, citation of publications, enforcement of violations, sharing of integrated data, and arbitration procedures for resolving disagreements. Researchers must apply for a license to gain access to the data, and approval is based on whether the data is appropriate for the proposed project, the academic non-commercial affiliation of the researcher, and acceptance of the conditions of use; around one-third of the applications are denied [177]. The researchers accessing the data sign a non-disclosure agreement, agreeing to use the data only for non-commercial purposes, not to attempt to identify the individuals, not to report statistics that would allow such identification, and not to redistribute the data to third parties. Violations of the agreement are subject to professional censure, loss of employment, civil prosecution, and to sanctions against the researcher's institution. IPUMS notes that with the supervision of IRBs and corresponding bodies in other countries, the lack of incentives for the researchers to identify the individuals, and with researchers' reputation at stake, abusing data is unlikely [178] and only few allegations have been ever made in the context of registry data.

No matter whether the data are accessed for research or commercial purposes, perfectly secure systems are virtually impossible to build. Even in top secret government agencies, there must exist people with sufficient access to extract very sensitive data; it is an operational reality. Whenever the data is shared, some aspects of ensuring the proper processing must rely on legal and business dimensions. The effectiveness of these varies, depending on the nature of the data and parties accessing them: respected researchers may have a lot to lose and little to gain from abusing the data, large commercial services may try to do it, even if they risk that their misconduct may be discovered.

7 Privacy Actionable Items

Here we present the executive summary for the practitioners of sensor-driven massive data collection studies involving human participants.

Regulations. When a new study is provisioned, it must follow the regulations of the proper authorities. Special attention should be given to the cases where the data may travel across borders, either as part

of the study operation (e.g. data storage) or as a part of research collaboration with foreign institutions. The requirements and guidelines may differ significantly between countries. Furthermore, if the data collection happens in one country and analysis of the dataset happens in another, the data analysis may not be considered a human subjects study, and thus may not require IRB approval. The regulations and guidelines of the country where the study is conducted reflect expectations of the participants regarding their data treatment. Researchers need to make sure that these are respected, even when the data flows across borders.

Informed Consent. Informed consent is the central point of the participant-researcher relation. We strongly encourage the publication of the informed consent procedure for the conducted studies, so the best practices can be built around it. As a research community, we should be working towards the implementation of Living Informed Consent, where the users are empowered to better understand and revisit their authorizations and their relation with the studies and services in general. This relation should ideally last for as long as the users' data exist in the dataset. As new techniques for data analysis are introduced and new insights can be gained from the same data, the participants should be made aware of, and possibly in charge of, the secondary use. Additionally, we envision a better alignment of business, legal, and technical dimensions of the informed consent, where the user's act of consenting is not only registered for legal purposes, but through technical means creates the required authorizations, e.g. OAuth2 tokens.

We do not expect or want users to spend hours staring into the screens to control the access to their data. Ensuring such metadata is available for the user is a necessary but not sufficient condition for a successful implementation of Living Informed Consent. Business, legal, and technical dimensions must be aligned to make the presented information accountable and actionable. The presentation layer must be carefully designed, with the UI as simple as possible, but not simpler than necessary to convey the privacy message. Finally, providing access to the metadata about data collection and usage, creates an opportunity for third parties to help the user to analyze, audit, understand, and change the privacy settings. There is a danger that providing raw access to the data and metadata will create an illusion of user control. Still, the improvement of the users' privacy has to start somewhere, and even if the initial implementations of Living Informed Consent are not perfect, they will create an opportunity to build better solutions upon them.

Security. Security of the data is crucial for ensuring privacy. Moving into the cloud may require close examination of the infrastructure provider's policy, as well as the technical solutions limiting access to the data in the shared-resources environment. One of the solutions is to encrypt the data on a server physically owned by the research unit conducting the studies, and only then pushing it into the cloud. There are different levels of encryption granularity that may be used. The less structure is preserved in the data, the less information can potentially leak, but at the same time, less meaningful queries or data processing can be executed on the encrypted data. It may be an option to encrypt (or one-way hash) only PII's, keeping the structure of the data and certain raw values (e.g. location coordinates). This allows for effective data querying in the database, but at the same time can expose the information about the participants (the cloud learns where the participants are, but doesn't learn their names or other PII's). If the data is encrypted in its entirety, effective queries become difficult and may not be feasible.

Privacy Implementation. The data collected is only valuable if it can be analyzed. It is often desired or necessary to share the data in some form with third parties, some of whom may be hostile. As it has been shown in multiple cases, de-identification, introducing the noise, implementing k -anonymity etc. may be insufficient against an educated and determined attacker (Attacks against Privacy section). We can expect this problem to grow, as more publicly available information is exposed by the participants in different (non-study-related) channels. If it is sufficient to know several locations to uniquely identify

the user [15], all the other data gathered in the study can then also be linked to the real person. Firstly, we suggest that good practice is to make the type of de-identification performed on the dataset public, helping to establish common practices and understanding of what works and what does not. One of the possible directions is to move away from copying the entire datasets for later offline analysis, which is becoming impractical anyway, due to large size and real-time nature of the data. Instead, researchers and other services can interact with the data through APIs that allow for control and accountability. If data dimensionality is additionally reduced before flowing through the API (e.g. city-level location of the user rather than raw GPS trace), privacy can be managed in a more robust way.

Contract Governance. The technical means employed for ensuring proper data processing, have their limitations. When the data is shared and used, it should be done under contracts defining researchers' and services' obligations and allowed uses. The threat of legal and business consequences should play a crucial role in implementing participants' privacy. Every party accessing the data should agree not to try to re-identify the users or otherwise abuse the data. Although this may seem naive, such agreements can be the most powerful factor in limiting abuses; in many cases researchers or other third parties have little to gain in abusing the data, while risking their reputation and the chance of lawsuits. It is desired to watermark the data separately for each share in order to support auditing. Contractual and watermarking practices have been adopted, to certain extent, in sharing medical, biological, and financial data. Depending on the nature of the data or pre-existing relation between primary researchers and the third party, the contract may need to be of a certain complexity combined with a practical auditing system. There is always a balance to be found between the difficulty of re-identification, potential harm to the participants, and gain from the conducted research. When the overhead of establishing legal contracts with all parties accessing the data is prohibitive, a minimal End-User License Agreement (EULA) should be used, where the researchers promise not to attempt re-identification, abuse the data, or share them further. Similarly to informed consent forms, we suggest making public the forms signed by parties accessing the data in the studies (contracts and EULAs), in order to establish best practices for this process.

Conclusions

In this article we have reviewed the privacy-related practices in existing sensor-driven studies of massive data collection involving human participants. It is clear that the size and resolution of studies grows quickly and for this reason the collected data should be considered increasingly sensitive. As the sensitivity of the data grows, better tools to support the privacy of the participants have to be developed.

In massive human data collection, the main concerns are currently technical solutions to scalability and data availability. Often, making the data available to researchers takes precedence over creating the right solutions for the many aspects of privacy that need to be addressed. Here, we have identified a number of concrete domains, which are crucial for implementation of good privacy practices. These include informed consent management, data security, auditing, or controlling information flows. We have reviewed tools that can support some of these requirements and noted that, for various reasons, they are not widely used. We feel that the adoption of reusable and common systems is necessary to improve the privacy situation in the field. Reusable tools and systems, as well as shared standards, will allow scientists and engineers to focus on research questions, rather than re-inventing the complex elements of privacy in a new era of massive data collection.

The underlying driver of the change has to be the end-user expression of informed consent and resulting orchestration of data processing in business, legal, and technical domains. In Living Informed Consent, participants in long-lasting studies with complex data flows will be able to express their preferences and monitor the results. Going beyond existing practices of obtaining the consent, the users have to be recognized as key stakeholders in the studies. In addition to promoting better privacy, this will be beneficial for the research community as well, allowing access to more data from the users, rather than

starting every collection from scratch. A key aspect of improving privacy has to be contract governance. Every flow, every data access should ideally be accounted for and possible to audit, matching it with the user authorizations existing at that time. Creating such systems, with perfect cooperation of technical and legal solutions is not easy. In every case, the threat of de-identification, potential harm to the users, and the reputation of the parties accessing the data should be balanced with the gains from the conducted research. Just as in any other science, robust, efficient, and workable privacy solutions have to be developed iteratively, as a process.

Here we laid the groundwork for the privacy management change process that can support such transformation. Although the article focused on the privacy practices in the research context, many of the identified challenges and solutions apply to other domains where the massive data collection takes place, including business and governmental contexts. Using the review as a starting point, we have constructed a list the most important challenges to overcome in data collection efforts. We are hopeful users will be put in charge of the data authorizations, and in the near future of the data itself. This will be a fundamental shift in the way science is done, and we can expect many studies will not necessarily involve actual data collection. Rather, the studies will become applications of already existing user data, managed and monitored by the users themselves. This is an important step towards the New Deal on Data, ensuring that the required data is available for the public good [179].

References

1. Lazer D, Pentland A, Adamic L, Aral S, Barabasi A, et al. (2009) Life in the network: the coming age of computational social science. *Science* (New York, NY) 323: 721.
2. Eagle N, Pentland AS, Lazer D (2009) Inferring friendship network structure by using mobile phone data. *Proceedings of the National Academy of Sciences* 106: 15274–15278.
3. Chronis I, Madan A, Pentland A (2009) Socialcircuits: the art of using mobile phones for modeling personal interactions. In: *Proceedings of the ICMI-MLMI'09 Workshop on Multimodal Sensor-Based Systems and Mobile Phones for Social Computing*. ACM, p. 1.
4. Wu L, Waber B, Aral S, Brynjolfsson E, Pentland A (2008) Mining face-to-face interaction networks using sociometric badges: Predicting productivity in an it configuration task. Available at SSRN 1130251 .
5. Pentland AS (2008) *Honest signals: how they shape our world*. MIT Press.
6. Raento M, Oulasvirta A, Eagle N (2009) Smartphones an emerging tool for social scientists. *Sociological methods & research* 37: 426–454.
7. Olguín D, Madan A, Cebrian M, Pentland A (2011) Mobile sensing technologies and computational methods for collective intelligence. *Next Generation Data Technologies for Collective Computational Intelligence* : 575–597.
8. Gordon E, Cooper N, Rennie C, Hermens D, Williams L (2005) Integrative neuroscience: the role of a standardized database. *Clinical EEG and Neuroscience* 36: 64–75.
9. Various Authors (2012) *The value of privacy*. MIT Technology Review - Business Report .
10. Krumm J (2009) A survey of computational location privacy. *Personal and Ubiquitous Computing* 13: 391–399.
11. Korth A, Baumann S, Nürnberger A (2011) An interdisciplinary problem taxonomy for user privacy in social networking services. In: *Workshop on Privacy for a Networked World*.

12. Narayanan A, Shmatikov V (2008) Robust de-anonymization of large sparse datasets. In: Security and Privacy, 2008. SP 2008. IEEE Symposium on. IEEE, pp. 111–125.
13. Sweeney L (2000) Simple demographics often identify people uniquely. *Health* (San Francisco) : 1–34.
14. Barbaro M, Zeller T, Hansell S (2006) A face is exposed for aol searcher no. 4417749. *New York Times* 9: 8For.
15. de Montjoye YA, Hidalgo CA, Verleysen M, Blondel VD (2013) Unique in the crowd: The privacy bounds of human mobility. *Scientific reports* 3.
16. Altshuler Y, Aharony N, Elovici Y, Pentland A, Cebrian M (2011) Stealing reality: when criminals become data scientists (or vice versa). *Security and Privacy in Social Networks* : 133–151.
17. Warren SD, Brandeis LD (1890) The right to privacy. *Harvard law review* 4: 193–220.
18. Westin AF, Blom-Cooper L (1970) Privacy and freedom. Bodley Head London.
19. Cate FH (1997) Privacy in the information age. Brookings Inst Press.
20. Aharony N, Pan W, Ip C, Khayal I, Pentland A (2011) Social fmri: Investigating and shaping social mechanisms in the real world. *Pervasive and Mobile Computing* .
21. Madan A, Cebrian M, Moturu S, Farrahi K, Pentland S (2011) Sensing the health state of a community. *Pervasive Computing* .
22. Eagle N, Pentland A (2006) Reality mining: sensing complex social systems. *Personal and Ubiquitous Computing* 10: 255–268.
23. Eagle N, Pentland A (2003) Social network computing. In: *UbiComp 2003: Ubiquitous Computing*. Springer, pp. 289–296.
24. Karikoski J, Nelimarkka M (2011) Measuring social relations with multiple datasets. *International Journal of Social Computing and Cyber-Physical Systems* 1: 98–113.
25. Aad I, Niemi V (2010) Nrc data collection and the privacy by design principles. *Proc of PhoneSense* : 41–45.
26. Kiukkonen N, Blom J, Dousse O, Gatica-Perez D, Laurila J (2010) Towards rich mobile phone datasets: Lausanne data collection campaign. *Proc ICPS, Berlin* .
27. Laurila J, Gatica-Perez D, Aad I, Blom J, Bornet O, et al. (2012) The mobile data challenge: Big data for mobile computing research. In: *Mobile Data Challenge by Nokia Workshop*, in conjunction with *Int. Conf. on Pervasive Computing*, Newcastle, UK.
28. Shakimov A, Lim H, Cáceres R, Cox LP, Li K, et al. (2011) Vis-a-vis: Privacy-preserving online social networking via virtual individual servers. In: *Communication Systems and Networks (COMSNETS), 2011 Third International Conference on*. IEEE, pp. 1–10.
29. Hong J, Landay J (2004) An architecture for privacy-sensitive ubiquitous computing. In: *Proceedings of the 2nd international conference on Mobile systems, applications, and services*. ACM, pp. 177–189.
30. Gemmell J, Bell G, Lueder R (2006) Mylifebits: a personal database for everything. *Communications of the ACM* 49: 88–95.

31. Gemmell J, Bell G, Lueder R, Drucker S, Wong C (2002) Mylifebits: fulfilling the memex vision. In: Proceedings of the tenth ACM international conference on Multimedia. ACM, pp. 235–238.
32. Popa R, Balakrishnan H, Blumberg A (2009) Vpriv: protecting privacy in location-based vehicular services. In: Proceedings of the 18th conference on USENIX security symposium. USENIX Association, pp. 335–350.
33. Rivest RL, Adleman L, Dertouzos ML (1978) On data banks and privacy homomorphisms. Foundations of secure computation 4: 169–180.
34. Molina A, Salajegheh M, Fu K (2009) Hiccups: health information collaborative collection using privacy and security. In: Proceedings of the first ACM workshop on Security and privacy in medical and home-care systems. ACM, pp. 21–30.
35. Miluzzo E, Cornelius C, Ramaswamy A, Choudhury T, Liu Z, et al. (2010) Darwin phones: the evolution of sensing and inference on mobile phones. In: Proceedings of the 8th international conference on Mobile systems, applications, and services. ACM, pp. 5–20.
36. Cornelius C, Kapadia A, Kotz D, Peebles D, Shin M, et al. (2008) Anonymsense: privacy-aware people-centric sensing. In: Proceedings of the 6th international conference on Mobile systems, applications, and services. ACM, pp. 211–224.
37. Kapadia A, Triandopoulos N, Cornelius C, Peebles D, Kotz D (2008) Anonymsense: Opportunistic and privacy-preserving context collection. Pervasive Computing : 280–297.
38. Sweeney L (2002) k-anonymity: A model for protecting privacy. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems 10: 557–570.
39. Mazzia A, LeFevre K, Adar E (2012) The pviz comprehension tool for social network privacy settings. In: Proceedings of the Eighth Symposium on Usable Privacy and Security. ACM, p. 13.
40. Kapadia A, Henderson T, Fielding J, Kotz D (2007) Virtual walls: Protecting digital privacy in pervasive environments. Pervasive Computing : 162–179.
41. Kagal L, Finin T, Joshi A (2003) A policy based approach to security for the semantic web. The Semantic Web-ISWC 2003 : 402–418.
42. Miluzzo E, Lane N, Fodor K, Peterson R, Lu H, et al. (2008) Sensing meets mobile social networks: the design, implementation and evaluation of the cenceme application. In: Proceedings of the 6th ACM conference on Embedded network sensor systems. ACM, pp. 337–350.
43. Ganti R, Pham N, Ahmadi H, Nangia S, Abdelzaher T (2010) Greengps: A participatory sensing fuel-efficient maps application. In: Proceedings of the 8th international conference on Mobile systems, applications, and services. ACM, pp. 151–164.
44. Ganti RK, Pham N, Tsai YE, Abdelzaher TF (2008) Poolview: stream privacy for grassroots participatory sensing. In: Proceedings of the 6th ACM conference on Embedded network sensor systems. ACM, pp. 281–294.
45. Vosoughi S, Goodwin MS, Washabaugh B, Roy D (2012) A portable audio/video recorder for longitudinal study of child development. In: Proceedings of the 14th ACM international conference on Multimodal interaction. ACM, pp. 193–200.
46. Roy D, Patel R, DeCamp P, Kubat R, Fleischman M, et al. (2006) The human speechome project. Symbol Grounding and Beyond : 192–196.

47. Kostakos V, O'Neill E (2008) Cityware: Urban computing to bridge online and real-world social networks. *Handbook of research on urban informatics: The practice and promise of the real-time city* : 195–204.
48. Quercia D, Capra L (2009) Friendsensing: recommending friends using mobile phones. In: *Proceedings of the third ACM conference on Recommender systems*. ACM, pp. 273–276.
49. Ypodimatopoulos P, Lippman A (2010) 'follow me': a web-based, location-sharing architecture for large, indoor environments. In: *Proceedings of the 19th international conference on World wide web*. ACM, pp. 1375–1378.
50. Toch E, Cranshaw J, Drielsma PH, Tsai JY, Kelley PG, et al. (2010) Empirical models of privacy in location sharing. In: *Proceedings of the 12th ACM international conference on Ubiquitous computing*. pp. 129–138.
51. Mahato H, Kern D, Holleis P, Schmidt A (2008) Implicit personalization of public environments using bluetooth. In: *CHI'08 extended abstracts on Human factors in computing systems*. ACM, pp. 3093–3098.
52. Friedman B, Lin P, Miller J (2005) Informed consent by design. *Security and Usability* : 495–521.
53. Beauchamp TL, Childress JF (2001) *Principles of biomedical ethics*. Oxford university press.
54. Utley GJAER, et al. (1992) The Nazi Doctors and the Nuremberg Code: Human Rights in Human Experimentation: Human Rights in Human Experimentation. Oxford University Press.
55. Faden RR, Beauchamp TL, King NM (1986) A history and theory of informed consent .
56. Applebaum PS, Lidz CW, Meisel A (1987) *Informed consent: Legal theory and clinical practice*. Oxford University Press.
57. Berg JW, Appelbaum PS, Lidz CW, Parker LS (2001) *Informed consent: legal theory and clinical practice* .
58. Madan A, Moturu ST, Lazer D, Pentland AS (2010) Social sensing: obesity, unhealthy eating and exercise in face-to-face networks. In: *Wireless Health 2010*. ACM, pp. 104–110.
59. Madan A, Farrahi K, Gatica-Perez D, Pentland A (2011) Pervasive sensing to model political opinions in face-to-face networks. *Pervasive Computing* : 214–231.
60. Olguín D, Waber B, Kim T, Mohan A, Ara K, et al. (2009) Sensible organizations: Technology and methodology for automatically measuring organizational behavior. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on* 39: 43–55.
61. Kotz D, Avancha S, Baxi A (2009) A privacy framework for mobile health and home-care systems. In: *Proceedings of the first ACM workshop on Security and privacy in medical and home-care systems*. ACM, pp. 1–12.
62. Böhme R, Köpsell S (2010) Trained to accept?: A field experiment on consent dialogs. In: *Proceedings of the 28th international conference on Human factors in computing systems*. ACM, pp. 2403–2406.
63. Cassileth BR, Zupkis RV, Sutton-Smith K, March V (1980) Informed consent—why are its goals imperfectly realized? *The New England journal of medicine* 302: 896–900.

64. Paasche-Orlow MK, Taylor HA, Brancati FL (2003) Readability standards for informed-consent forms as compared with actual readability. *New England journal of medicine* 348: 721–726.
65. Sugarman J, McCrory DC, Powell D, Krasny A, Adams B, et al. (1999) Empirical research on informed consent: an annotated bibliography. *Hastings Center Report* 29: s1–s42.
66. Lavori PW, Sugarman J, Hays MT, Feussner JR (1999) Improving informed consent in clinical trials: a duty to experiment. *Controlled clinical trials* 20: 187–193.
67. Egelman S, Felt A, Wagner D (2012) Choice architecture and smartphone privacy: Theres a price for that. In: *Workshop on the Economics of Information Security (WEIS)*.
68. Felt A, Greenwood K, Wagner D (2011) The effectiveness of application permissions. In: *Proc. of the USENIX Conference on Web Application Development*.
69. Cranor L (2006) What do they indicate?: evaluating security and privacy indicators. *interactions* 13: 45–47.
70. Flory J, Emanuel E (2004) Interventions to improve research participants' understanding in informed consent for research. *JAMA: the journal of the American Medical Association* 292: 1593–1601.
71. for the Protection of Human Subjects of Biomedical NC, Behavioral Research M Bethesda (1978) The Belmont report: Ethical principles and guidelines for the protection of human subjects of research. ERIC Clearinghouse.
72. Saif M, et al. (2000) World medical association declaration of helsinki: ethical principles for medical research involving human subjects. *Jama* 284: 3043–3045.
73. Dunn LB, Lindamer LA, Palmer BW, Golshan S, Schneiderman LJ, et al. (2002) Improving understanding of research consent in middle-aged and elderly patients with psychotic disorders. *The American journal of geriatric psychiatry* 10: 142–150.
74. Agre P, Campbell FA, Goldman BD, Boccia ML, Kass N, et al. (2003) Improving informed consent: the medium is not the message. *IRB: Ethics and Human Research* 25: S11–S19.
75. Fureman I, Meyers K, McLellan AT, Metzger D, Woody G (1997) Evaluation of a video-supplement to informed consent: injection drug users and preventive hiv vaccine efficacy trials. *AIDS education and prevention: official publication of the International Society for AIDS Education* 9: 330–341.
76. Weston J, Hannah M, Downes J (1997) Evaluating the benefits of a patient information video during the informed consent process. *Patient education and counseling* 30: 239–245.
77. Shabajee P (2006) Informed consent on the semantic web-issues for interaction and interface designers. In: *3rd International Semantic Web User Interaction Workshop*. <http://swui.semanticweb.org/swui06/papers/Shabajee/Shabajee.pdf> (retrieved 15.11. 10).
78. Lindqvist J, Cranshaw J, Wiese J, Hong J, Zimmerman J (2011) I'm the mayor of my house: examining why people use foursquare-a social-driven location sharing application. In: *Proceedings of the 2011 annual conference on Human factors in computing systems*. ACM, pp. 2409–2418.
79. Avancha S, Baxi A, Kotz D (2009) Privacy in mobile technology for personal healthcare. Submitted to *ACM Computing Surveys*.

80. Toch E, Sadeh N, Hong J (2010) Generating default privacy policies for online social networks. In: Proceedings of the 28th of the international conference extended abstracts on Human factors in computing systems. ACM, pp. 4243–4248.
81. de Montjoye YA, Wang SS, Pentland A, Anh DTT, Datta A, et al. (2012) On the trusted use of large-scale personal data. *IEEE Data Eng Bull* 35: 5–8.
82. Siminoff LA (2003) Toward improving the informed consent process in research with humans. *IRB: Ethics and Human Research* 25: S1–S3.
83. Hayden EC (2012). "informed consent: A broken contract". URL <http://www.nature.com/news/informed-consent-a-broken-contract-1.10862>.
84. (2012). "time to open up". doi:doi:10.1038/486293a. URL <http://www.nature.com/nature/journal/v486/n7403/full/486293a.html>.
85. Lunshof JE, Chadwick R, Vorhaus DB, Church GM (2008) From genetic privacy to open consent. *Nature Reviews Genetics* 9: 406–411.
86. (2013). "critics urge caution as uk genome project hunts for volunteers". URL <http://www.theguardian.com/science/2013/nov/07/personal-genome-project-uk-launch>.
87. Drummond DC (2009) Replicability is not reproducibility: Nor is it good science .
88. Reinhart CM, Rogoff KS (2010) Growth in a time of debt. Technical report, National Bureau of Economic Research.
89. Donohue J, Levitt SD (2001) The impact of legalized abortion on crime. *Quarterly Journal of Economics* 116.
90. Bertrand KZ, Bialik M, Virdee K, Gros A, Bar-Yam Y (2013) Sentiment in new york city: A high resolution spatial and temporal view. arXiv preprint arXiv:13085010 .
91. BOHANNON J (2013). ScienceShot: The Saddest Spot in New York. <http://news.sciencemag.org/brain-behavior/2013/08/scienceshot-saddest-spot-new-york>.
92. Bissell M (2013) Reproducibility: The risks of the replication drive. *Nature* 503: 333–334.
93. Klasnja P, Consolvo S, Choudhury T, Beckwith R, Hightower J (2009) Exploring privacy concerns about personal sensing. *Pervasive Computing* : 176–183.
94. Felt A, Ha E, Egelman S, Haney A, Chin E, et al. (2012) Android permissions: User attention, comprehension, and behavior. In: Proceedings of the Eighth Symposium on Usable Privacy and Security. ACM, p. 3.
95. Shapiro R, Ossorio P (2013) Regulation of online social network studies. *Science* 339: 144–145.
96. Underwood MK, Rosen LH, More D, Ehrenreich SE, Gentsch JK (2012) The blackberry project: Capturing the content of adolescents' text messaging. *Developmental psychology* 48: 295.
97. Stutzman F, Gross R, Acquisti A (2013) Silent listeners: The evolution of privacy and disclosure on facebook. *Journal of Privacy and Confidentiality* 4: 2.

98. Scarfone K, Hoffman P (2009) Guidelines on firewalls and firewall policy. NIST Special Publication 800: 41.
99. Scarfone K, Mell P (2007) Guide to intrusion detection and prevention systems (idps). NIST Special Publication 800: 94.
100. Hay B, Nance K, Bishop M (2011) Storm clouds rising: security challenges for iaas cloud computing. In: System Sciences (HICSS), 2011 44th Hawaii International Conference on. IEEE, pp. 1–7.
101. Fernando N, Loke SW, Rahayu W (2012) Mobile cloud computing: A survey. Future Generation Computer Systems .
102. Calluru Rajasekar N, Imafidon C (2010) Exploitation of vulnerabilities in cloud storage. In: CLOUD COMPUTING 2010, The First International Conference on Cloud Computing, GRIDs, and Virtualization. pp. 122–127.
103. Hashizume K, Rosado DG, Fernández-Medina E, Fernandez EB (2013) An analysis of security issues for cloud computing. Journal of Internet Services and Applications 4: 5.
104. Ristenpart T, Tromer E, Shacham H, Savage S (2009) Hey, you, get off of my cloud: exploring information leakage in third-party compute clouds. In: Proceedings of the 16th ACM conference on Computer and communications security. ACM, pp. 199–212.
105. King ST, Chen PM (2006) Subvirt: Implementing malware with virtual machines. In: Security and Privacy, 2006 IEEE Symposium on. IEEE, pp. 14–pp.
106. Aviram A, Hu S, Ford B, Gummadi R (2010) Determinating timing channels in compute clouds. In: Proceedings of the 2010 ACM workshop on Cloud computing security workshop. ACM, pp. 103–108.
107. Zhang Y, Juels A, Reiter MK, Ristenpart T (2012) Cross-vm side channels and their use to extract private keys. In: Proceedings of the 2012 ACM conference on Computer and communications security. ACM, pp. 305–316.
108. Hull B, Bychkovsky V, Zhang Y, Chen K, Goraczko M, et al. (2006) Cartel: a distributed mobile sensor computing system. In: Proceedings of the 4th international conference on Embedded networked sensor systems. ACM, pp. 125–138.
109. Raij A, Ghosh A, Kumar S, Srivastava M (2011) Privacy risks emerging from the adoption of innocuous wearable sensors in the mobile environment. In: Proceedings of the 2011 annual conference on Human factors in computing systems. ACM, pp. 11–20.
110. Lane N, Xie J, Moscibroda T, Zhao F (2012) On the feasibility of user de-anonymization from shared mobile sensor data. In: Proceedings of the Third International Workshop on Sensing Applications on Mobile Phones. ACM, p. 3.
111. de Montjoye YA, Quoidbach J, Robic F, Pentland AS (2013) Predicting personality using novel mobile phone-based metrics. In: Social Computing, Behavioral-Cultural Modeling and Prediction, Springer. pp. 48–55.
112. Li T, Li N (2009) On the tradeoff between privacy and utility in data publishing. In: Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, pp. 517–526.

113. Fung B, Wang K, Chen R, Yu PS (2010) Privacy-preserving data publishing: A survey of recent developments. *ACM Computing Surveys (CSUR)* 42: 14.
114. Agrawal R, Srikant R (2000) Privacy-preserving data mining. In: *ACM Sigmod Record*. ACM, volume 29, pp. 439–450.
115. Agrawal D, Aggarwal CC (2001) On the design and quantification of privacy preserving data mining algorithms. In: *Proceedings of the twentieth ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems*. ACM, pp. 247–255.
116. Evfimievski A, Gehrke J, Srikant R (2003) Limiting privacy breaches in privacy preserving data mining. In: *Proceedings of the twenty-second ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems*. ACM, pp. 211–222.
117. Dinur I, Nissim K (2003) Revealing information while preserving privacy. In: *Proceedings of the twenty-second ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems*. ACM, pp. 202–210.
118. Dwork C, Nissim K (2004) Privacy-preserving datamining on vertically partitioned databases. In: *Advances in Cryptology—CRYPTO 2004*. Springer, pp. 134–138.
119. Blum A, Dwork C, McSherry F, Nissim K (2005) Practical privacy: the sqlq framework. In: *Proceedings of the twenty-fourth ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems*. ACM, pp. 128–138.
120. Dwork C, Kenthapadi K, McSherry F, Mironov I, Naor M (2006) Our data, ourselves: Privacy via distributed noise generation. *Advances in Cryptology-EUROCRYPT 2006* : 486–503.
121. Chawla S, Dwork C, McSherry F, Smith A, Wee H (2005) Toward privacy in public databases. *Theory of Cryptography* : 363–385.
122. Chawla S, Dwork C, McSherry F, Talwar K (2012) On privacy-preserving histograms. *arXiv preprint arXiv:12071371* .
123. Stopczynski A, Sekara V, Sapiezynski P, Cuttone A, Larsen JE, et al. (2014) Measuring large-scale social networks with high resolution. *arXiv preprint arXiv:14017233* .
124. Shokri R, Theodorakopoulos G, Le Boudec J, Hubaux J (2011) Quantifying location privacy. In: *Security and Privacy (SP), 2011 IEEE Symposium on*. IEEE, pp. 247–262.
125. Machanavajjhala A, Kifer D, Gehrke J, Venkatasubramanian M (2007) l -diversity: Privacy beyond k -anonymity. *ACM Transactions on Knowledge Discovery from Data (TKDD)* 1: 3.
126. Li N, Li T, Venkatasubramanian S (2007) t -closeness: Privacy beyond k -anonymity and l -diversity. In: *Data Engineering, 2007. ICDE 2007. IEEE 23rd International Conference on*. IEEE, pp. 106–115.
127. Cavoukian A, El Emam K (2011) Dispelling the Myths Surrounding De-identification: Anonymization Remains a Strong Tool for Protecting Privacy. Information and Privacy Commissioner of Ontario, Canada.
128. Gentry C (2009) A fully homomorphic encryption scheme. Ph.D. thesis, Stanford University.
129. Franz M, Deiseroth B, Hamacher K, Jha S, Katzenbeisser S, et al. (2012) Secure computations on non-integer values with applications to privacy-preserving sequence analysis. *Information Security Technical Report* .

130. TEBA A M, EL HAJJI S, EL GHAZI A (2012) Homomorphic encryption applied to the cloud computing security. *Lecture Notes in Engineering and Computer Science* 2197.
131. Naehrig M, Lauter K, Vaikuntanathan V (2011) Can homomorphic encryption be practical? In: *Proceedings of the 3rd ACM workshop on Cloud computing security workshop*. ACM, pp. 113–124.
132. Srivatsa M, Hicks M (2012) Deanonimizing mobility traces: using social network as a side-channel. In: *Proceedings of the 2012 ACM conference on Computer and communications security*. ACM, pp. 628–637.
133. Mislove A, Viswanath B, Gummadi KP, Druschel P (2010) You are who you know: inferring user profiles in online social networks. In: *Proceedings of the third ACM international conference on Web search and data mining*. ACM, pp. 251–260.
134. Tene O, Polonetsky J (2012) Big data for all: Privacy and user control in the age of analytics. *Northwestern Journal of Technology and Intellectual Property*, Forthcoming .
135. Aggarwal CC, Abdelzaher T Social sensing. *Managing and Mining Sensor Data* .
136. Kosinski M, Stillwell D, Graepel T (2013) Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences* 110: 5802–5805.
137. Zhou B, Pei J (2008) Preserving privacy in social networks against neighborhood attacks. In: *Data Engineering, 2008. ICDE 2008. IEEE 24th International Conference on*. IEEE, pp. 506–515.
138. Cheng J, Fu AWc, Liu J (2010) K-isomorphism: privacy preserving network publication against structural attacks. In: *Proceedings of the 2010 ACM SIGMOD International Conference on Management of data*. ACM, pp. 459–470.
139. Davis Jr CA, Pappa GL, de Oliveira DRR, de L Arcanjo F (2011) Inferring the location of twitter messages based on user relationships. *Transactions in GIS* 15: 735–751.
140. Zheleva E, Getoor L (2009) To join or not to join: the illusion of privacy in social networks with mixed public and private user profiles. In: *Proceedings of the 18th international conference on World wide web*. ACM, pp. 531–540.
141. Chester S, Srivastava G (2011) Social network privacy for attribute disclosure attacks. In: *Advances in Social Networks Analysis and Mining (ASONAM), 2011 International Conference on*. IEEE, pp. 445–449.
142. Qiu L, Zhang Y, Wang F, Kyung M, Mahajan HR (1985) Trusted computer system evaluation criteria. In: *National Computer Security Center*. Citeseer.
143. Kotz D (2011) A threat taxonomy for mhealth privacy. In: *Communication Systems and Networks (COMSNETS), 2011 Third International Conference on*. IEEE, pp. 1–6.
144. Duckham M (2010) Moving forward: location privacy and location awareness. In: *Proceedings of the 3rd ACM SIGSPATIAL International Workshop on Security and Privacy in GIS and LBS*. ACM, pp. 1–3.
145. Zdancewic SA (2002) *Programming languages for information security*. Ph.D. thesis, Cornell University.
146. Sfaxi L, Abdellatif T, Robbana R, Lakhnech Y (2010) Information flow control of component-based distributed systems. *Concurrency and Computation: Practice and Experience* .

147. Zeldovich N, Boyd-Wickizer S, Mazieres D (2008) Securing distributed systems with information flow control. NSDI.
148. Zhang Q, McCullough J, Ma J, Scheer N, Vrabie M, et al. (2010) Neon: system support for derived data management. In: ACM Sigplan Notices. ACM, volume 45, pp. 63–74.
149. Konings B, Piendl D, Schaub F, Weber M (2011) Privacyjudge: Effective privacy controls for on-line published information. In: Privacy, security, risk and trust (passat), 2011 IEEE third international conference on and 2011 IEEE third international conference on social computing (socialcom). IEEE, pp. 935–941.
150. Mundada Y, Ramachandran A, Feamster N (2011) Silverline: Data and network isolation for cloud services. Proc of 3rd HotCloud .
151. Pappas V, Kemerlis V, Zavou A, Polychronakis M, Keromytis AD (2012) Cloudfence: Enabling users to audit the use of their cloud-resident data .
152. Ganjali A, Lie D (2012) Auditing cloud administrators using information flow tracking .
153. Krohn M, Yip A, Brodsky M, Cliffer N, Kaashoek MF, et al. (2007) Information flow control for standard os abstractions. In: ACM SIGOPS Operating Systems Review. ACM, volume 41, pp. 321–334.
154. Demsky B (2011) Cross-application data provenance and policy enforcement. ACM Transactions on Information and System Security (TISSEC) 14: 6.
155. Castelluccia C, De Cristofaro E, Francillon A, Kaafar MA (2011) Ephpub: Toward robust ephemeral publishing. In: Network Protocols (ICNP), 2011 19th IEEE International Conference on. IEEE, pp. 165–175.
156. Boneh D, Lipton R (1996) A revocable backup system. In: USENIX Security Symposium. pp. 91–96.
157. Perlman R (2005) The ephemerizer: Making data disappear .
158. Perlman R (2005) File system design with assured delete. In: Security in Storage Workshop, 2005. SISW'05. Third IEEE International. IEEE, pp. 6–pp.
159. Geambasu R, Kohno T, Levy A, Levy HM (2009) Vanish: Increasing data privacy with self-destructing data. In: Proc. of the 18th USENIX Security Symposium. p. 56.
160. Naor M, Shamir A (1995) Visual cryptography. In: Advances in CryptologyEUROCRYPT'94. Springer, pp. 1–12.
161. Wolchok S, Hofmann OS, Heninger N, Felten EW, Halderman JA, et al. (2010) Defeating vanish with low-cost sybil attacks against large dhds. In: Proc. of NDSS.
162. Tang Y, Lee P, Lui J, Perlman R (2012) Secure overlay cloud storage with access control and assured deletion .
163. Agrawal R, Haas PJ, Kiernan J (2003) Watermarking relational data: framework, algorithms and analysis. The VLDB journal 12: 157–169.
164. Cox IJ, Miller ML, Bloom JA (2000) Watermarking applications and their properties. In: Information Technology: Coding and Computing, 2000. Proceedings. International Conference on. IEEE, pp. 6–10.

165. Cox IJ, Linnartz JP (1998) Some general methods for tampering with watermarks. *Selected Areas in Communications, IEEE Journal on* 16: 587–593.
166. Guo F, Wang J, Zhang Z, Ye X, Li D (2006) An improved algorithm to watermark numeric relational data. In: *Information Security Applications*, Springer. pp. 138–149.
167. White J, Thompson D (2006) Using synthetic decoys to digitally watermark personally-identifying data and to promote data security. In: *Security and Management*. pp. 91–99.
168. Sharad K, Danezis G De-anonymizing d4d datasets .
169. (2012). the other challenge: providing information while respecting privacy. <http://www.orange.com/en/D4D/Folder/anonymous-data>.
170. Hundepool A, de Wolf PP (2005) Onsite@ home: Remote access at statistics netherlands. *Monographs of official statistics* : 47.
171. Borchsenius L (2005) New developments in the danish system for access to micro data. *Monographs of official statistics* : 13–20.
172. Hjelm CG (2005) Mona-microdata on-line access at statistics sweden. *Monographs of official statistics* : 21–28.
173. Regulation C (1997) Council regulation (ec) no 322/97 of 17 february 1997 on community statistics. *Official Journal L* 52: 1–7.
174. Directive E (1995) 95/46/ec of the european parliament and of the council of 24 october 1995 on the protection of individuals with regard to the processing of personal data and on the free movement of such data. *Official Journal of the EC* 23: 6.
175. Fitzgerald AM, Pappalardo KM, Fitzgerald BF, Austin AC, Abbot JW, et al. (2007) Building the infrastructure for data access and reuse in collaborative research: An analysis of the legal context .
176. Ruggles S, King ML, Levison D, McCaa R, Sobek M (2003) Ipums-international. *Historical Methods: A Journal of Quantitative and Interdisciplinary History* 36: 60–65.
177. McCaa R, Esteve A (2005) Ipums-europe: Confidentiality measures for licensing and disseminating restricted-access census microdata extracts to academic users. *Monographs of official statistics: Work session on statistical data confidentiality* : 37–46.
178. Dale A, Elliot M (2001) Proposals for 2001 samples of anonymized records: an assessment of disclosure risk. *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 164: 427–447.
179. Pentland A (2009) Reality mining of mobile communications: Toward a new deal on data. *The Global Information Technology Report 2008–2009* : 1981.

APPENDIX I

Privacy for Personal Neuroinformatics

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Privacy for Personal Neuroinformatics

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Abstract

Human brain activity collected in the form of Electroencephalography (EEG), even with low number of sensors, is an extremely rich signal. Traces collected from multiple channels and with high sampling rates capture many important aspects of participants' brain activity and can be used as a unique personal identifier, similarly to fingerprints, DNA, or a portrait. The motivation for sharing EEG signals is significant, as a mean to understand the relation between brain activity and well-being, or for communication with medical services. However, only a small part of the brain activity is under voluntary control, thus the information revealed by EEG may largely be unknown to the user. As the equipment for such data collection becomes more available and widely used, the opportunities for using the data are growing; at the same time however inherent privacy risks are mounting. The same raw EEG signal can be used for example to diagnose mental diseases, find traces of epilepsy, and decode personality traits. The current practice of the informed consent of the participants for the use of the data either prevents reuse of the raw signal or does not truly respect participants' right to privacy by reusing the same raw data for purposes much different than originally consented to. This becomes even a bigger problem as the data lives on and new processing methods can extract information that was not deemed possible previously.

Here we propose an integration of a personal neuroinformatics system, Smartphone Brain Scanner, with a general privacy framework openPDS. We show how raw high-dimensionality data can be collected on a mobile device, uploaded to a server, and subsequently operated on and accessed by applications or researchers, without disclosing the raw signal. Those extracted features of the raw signal, called answers, are of significantly lower-dimensionality, and provide the full utility of the data in given context, without the risk of disclosing sensitive raw signal. Such architecture significantly mitigates a very serious privacy risk related to raw EEG recordings floating around and being used and reused for various purposes.

Introduction

Electroencephalography (EEG) is a method of recording brain activity as electrical signals, using electrodes placed around the scalp. The technique has been used for almost a century, with the first historic recording of human brain activity performed in 1924 by Hans Berger [1]. Since then, the use of EEG has flourished for both research and medical purposes.

Apart from a few notable application areas, such as sleep monitoring [2], it is only recently that EEG has moved outside of the laboratory, with the arrival of low-cost user-oriented neuroheadsets, powerful mobile devices, software frameworks, online services, and methods for data analysis. Health informatics providers such as Cure4You Technologies¹ are already facilitating storage and interaction with data from health apps.

Datasets of brain activity are being created and made available for analysis and services are starting to be built around EEG data. While sharing of scientific EEG data is well motivated [3], a strong motivation for sharing may also be present for an individual who acquires EEG data as 'self-quantification'. As EEG analysis is complex and users may be motivated to share data to seek help from the 'wisdom of the crowd' for interpreting relations between the EEG and health variability. Or they may use EEG data to enrich and qualify consultation with professionals [4]. A recent poll made by Pew Internet Projects shows that

¹<http://us.cure4you.pro>

peer-to-peer health care is already extensive in the US². Professional web services for physicians such as Sermo³ are increasingly quantitative and based on a data sharing.

These development raise questions about proper handling of EEG data and the privacy of users. Thus the contribution of this article is two-fold. First, we review privacy issues related to EEG data, caused by the inherent properties of the signal as well as the way it is collected and used. Second, we propose a framework for controlled sharing of data; acquiring EEG from low-cost mobile neuroheadsets, such as the Smartphone Brain Scanner [5], can be combined with open Personal Data System (openPDS), created for privacy-aware handling of personal data [6] backed by technical and legal means.

Sensitive Use

Why is there a special need for a privacy solution in relation to EEG? In contrast to more conventional sharing of text, imagery, and video, EEG is only partly under voluntary control, hence a user sharing EEG data may only in part comprehend what is being shared. For conventional data the user can build a mental model of shared content rooted in intuition from everyday social interaction. This means that sharing may not only be voluntary and transparent, it may in fact be used as efficient personal branding [7]. Recent reports on inference of more sensitive hidden variables from conventional social media content, e.g., inference of personality factors [8], show that such sharing is complex. But these findings do not rule out that users are aware that the content give away personal characteristics.

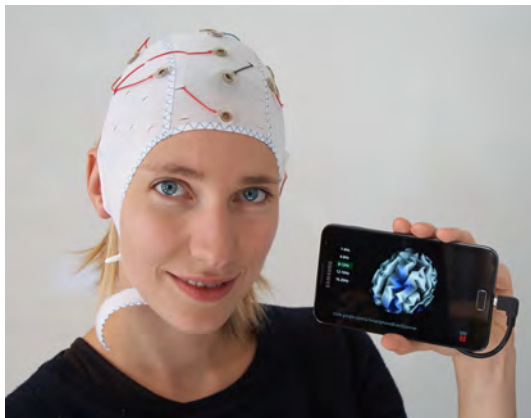


Figure 1. Mobile EEG brain imaging system, Smartphone Brain Scanner. Visible in the picture is the entire setup required for data acquisition, processing, and visualization. The cap contains gel-based electrodes used for acquiring electrical signal generated in brain and reaching the scalp. From [9]).

With EEG data, however, the situation is very different as the major parts of the signal are involuntary. In fact, the very ability to control minute portions of the variance is the mechanism behind so-called

²<http://www.pewinternet.org/Reports/2013/Health-online/Summary-of-Findings.aspx>

³<http://www.sermo.com/>

brain-computer interfaces (BCI) where sophisticated machine learning methods are needed to extract the induced components, see e.g., [10].

If we have synchronized, concurrent recordings of EEG and video/behavioral data, the EEG data become grounded, i.e., symbolic in nature, meaning that the information content can be much higher than raw bit rate [11].

What inferences can be made from EEG? Maybe the most sensitive are related to the diagnostic value of EEG. EEG has been used for diagnosing various mental diseases. As early as in 1988, Karson et al. described the use of EEG for diagnosing schizophrenia, based on increased activity in frequency bands known as delta and beta and decreased activity in the so-called alpha band [12]. The study was performed using 20 electrodes on 19 medication-free patients and 21 controls. Those results have been confirmed and extended in other studies, such as in [13], conducted on 44 first-episode and 58 chronic patients and 102 controls. The data in this study was collected merely from three electrodes for three minutes.

Dauwels et al. classified in [14] “mild cognitive impairment”, a precursor for Alzheimer’s disease. Gotlib et al. in [15] investigated the asymmetry in the alpha frequency in the frontal region as a possible biomarker for depression. The recordings were performed from three electrodes for eight minutes (with data cleaned for electrical artifacts as contaminated epochs were deleted). Many studies have investigated the usage of EEG in depression diagnosis, for an overview see [16].

EEG is a well established technique for diagnosing epilepsy [17]. Different EEG setups (number of recording electrodes, positioning, recording time, stimulus) are required for different kinds of epilepsy [18, 19]. In many cases, however, the basic diagnosis can be obtained with a relatively low number of electrodes (around 20), as typically the seizures affect major part of the cortex.

An important complication of EEG signals is that they are highly personal like fingerprints, DNA, or portraits, thus EEG recordings can be used for identification and authentication of the users.

Revet et al. [20] describe cognitive biometrics, utilizing a biosignal approach to user identification. The EEG signal shows identification accuracy of around 80%-100% [21] when using neural network classifier (LVQ) on the spectral values obtained from the alpha rhythm band of the EEG signal, broken into subbands. These classification rates were obtained with just two leads (O2 and CZ), and a few minutes of signal. Similarly, [22] reported 100% classification accuracy for 40 healthy subjects with all data and 80% using 50-50 split for cross-validation. These data were obtained from eight electrodes, using around one-minute-long recordings and autoregressive models. Investigating authentication rather than identification in [23], Marcel & Millán reviewed the usefulness of mental tasks for authentication purposes. This was done using an EEG system with eight electrodes, and machine learning models, on nine subjects. The performance of the authentication degraded over time (between template recording and authentication attempt), but with data from multiple days overall performance improved.

In [24] De Gennaro et al. showed that humans have an individual profile of the EEG spectra in the 8 - 16Hz frequency during non-rapid eye movement sleep, stable over time and resistant to experimental changes. The recordings were performed using 19 electrodes. This indicates the brain activity profile during sleep is highly unique and can be used to fingerprint people. Their findings were confirmed in [25], demonstrating the pattern of the EEG power distribution in non-REM sleep is characteristic for an individual.

Thus, EEG data appear to be highly unique to an individual and thus should be considered extremely sensitive. The ability to identify subjects in data sets may give the ability to match a short recording of the EEG data with data stored in the large sets, and, if the various types of data are linked, also to link to other information about the user, such as mobility traces or demographics [26, 27].

Using more direct attacks to reveal EEG information, Martinovic et al. investigated in [28] how the brain’s response to a particular stimulus (so-called P300 paradigm) can be used to narrow down the space of possible values of sensitive information such as PIN numbers, date of birth, or known people. The tasks required the subject to follow the experimental procedure without explicitly revealing the goal of

the experiment: for example thinking about birth date while watching flashing numbers. Although the presented attacks on the data may not be directly applicable to preexisting EEG data, as they require fairly specific malicious tasks, we can expect — as the subjects participate in multiple experiments — correlations violating privacy could be obtained from raw EEG signal. For example, when a large corpus of the user responses to a visual stimuli is collected, it could be used in P300-based Guilty-Knowledge Test, where the familiar items evoke different responses than similar but unfamiliar items [29].

In [30], the authors showed the detection of autobiographical information based on P300 paradigm. The detection of high-impact, autobiographical information — possibly more sensitive — was more reliable than detection of well-rehearsed but low impact, incidental information. When considering extracting information from the brain activity signal using P300 and related paradigms, the most important pieces may be the ones most easily revealed, invoking the strongest response.

Frank et al. explored in [31] feasibility of subliminal attacks, where the reaction to a short-lasting information of 13.3 milliseconds was measured. Such stimuli, in theory below conscious perception, could potentially be embedded multiple times in a standard, consciously perceived, stimuli and remain undetected. Authors showed promising results of recovering whether participants were familiar with a face, analyzing the response evoked by short-lasting stimuli hidden in the video frames.

The brain and the EEG are very far from understood; methods for more accurate analysis of EEG appear on a regular basis. As we learn to decode more and more advanced cognitive functions, such as the relation between the brain activity and linguistics [32], emotions [33], or psychological traits [34] it should be clear that we will be able to make unexpected and sensitive inferences from raw EEG signal in the future. Those who have shared raw EEG publicly are likely to have sensitive personal information lurking in the those data.

We note that in several of the mentioned case studies described above, significant knowledge about an individual has been extracted from relatively short recordings with a low number of electrodes. Thus, a high number of electrodes and professional grade systems may often not be necessary to ‘decode’ subjects, their mental health, high-level mental processing, and to uniquely identify them.

New Class of EEG Services and Datasets

Classically, most of the shared EEG datasets have been created as part of scientific experiments with a relatively low number of participants (say, less than a few hundred participants) and without linking the data to other personal data sources. Such datasets are usually frozen, in a sense that no new data are added to them and during their creation the data were not accessed for the purpose of analysis or building user-facing applications. Repositories of such datasets can be found, for example, at [35] or [36].

This situation is, however, changing, as data start to be collected from larger populations, in a form linked to the individual users, and available for real-time access. For example, *Emotiv Lifesciences* is a company set up by the creators of the Emotiv EEG neuroheadset with the mission of “... offering a unique platform for crowd-sourced brain research. Emotiv leverages cloud computing, big data and mobile technology to offer valuable personal insights and accelerate brain research globally.” [37]. MyZeo used to produce an EEG-based headband for sleep monitoring [38], the company does not operate anymore, it however used to allow for data uploading and analysis, providing a service of sleep logging. Even more companies enter the market, producing the headsets and headbands based on low-density EEG, for example Interaxon producing the Muse band⁴ or Melon⁵. Such data do not exist primarily in a form of a frozen, stable dataset, which may be easier to anonymize, for example using Principle Component Analysis (PCA) [39]. For the growing data that can be accessed by multiple applications and can be linked with other data sources, the standard anonymization techniques may not be sufficient.

Massive EEG databases containing recordings from thousands of participants are also being build for

⁴<http://interaxon.ca/>

⁵<http://www.usemelon.com/>

research purposes. Brain Resource Database [40]⁶, integrates information from neuroimaging measures (EEG, ERPs, MRI, and fMRI), arousal (heart rate, respiration, skin conductance responses), neurophysiological and personality tests, genomics, demographics. The database includes the data from over 2,000 normative subjects and number of patients with neurological and psychiatric illnesses. Another example is Australian EEG Database [41], advertised to contain 18,500 EEG recordings and available in a de-identified form.

A great opportunity in linked databases, containing synchronized behavioral and EEG data, is to be able to effectively move from analyzing the weak signals of ongoing free EEG to the much more informative evoked response signals. In this approach, long-term recordings of EEG data can be augmented with data potentially indicating events that stimulated the brain activations. In this context, the EEG and other personal data start blending together, allowing for much more complex modeling of human behavior. Techniques such as parallel factor analysis can be used to extract weak signals from variable responses [42]. Achieving a perfect synchronization between EEG signal and behavioral data is very hard; many of the signals collected have naturally different timescales, and the corresponding sensors may not even be able to record with certain resolutions. In addition, perfect timestamping of the events is difficult, especially on mobile systems that do not provide real-time guarantees. Shift-invariant multilinear decomposition can be used to analyze such signals, by introducing small adaptive shifts of time series to allow temporal alignment of EEG and behavioral variables [43].

We are at an early stage of personal data acquisition and sharing, and do not fully understand how the large EEG databases and services will impact the privacy of the participants: How unique users from a general population are in such data, how much can be inferred about the individual, who controls the flow of data and use of the subsequent results. As EEG analysis methods mature, even more so than what is usually understood as personal data (e.g. location, friendship graph), access to the raw EEG data will result in very different findings than originally anticipated. This poses both technical and legal challenges, as the policies developed for datasets, considered to be owned by the researchers or other third parties, such as described in [44], do not fully apply. Here we argue EEG data should be considered personal data, remaining, as much as possible, under the control of the user.

After all, what is personal if not an individual's thoughts?

New Privacy

Here we describe how a system for collection of EEG data from low-cost consumer-oriented neuroheadsets, such as the Smartphone Brain Scanner, can be seen as a personal data collection tool and linked to an openPDS backend solution. In the proposed architecture, the raw data collected by the participants is stored on the server under user control. The control is enforced by technical (e.g. self-hosting or encryption) and legal (e.g. terms of service, contract) means. The data can be accessed for the purpose of analysis and by user-facing applications, subject to participants' grant of authorization. Importantly, the raw data are not exposed. Instead high-level extracted features of the data are only transferred outside of user control as shown in Figure 2. This solution promotes the privacy of the user, while at the same time offering the full utility of the data, as additional questions (extracting the high-level features from the raw data) can be installed by the users from the third party services. It also effectively creates a service offering access to EEG data in a privacy-preserving way. In many cases, the features extracted from the EEG signal, for example Independent Components (ICs), are of real interest to the researchers or application developers [45], and those can be computed in the PDS, under user control. In fact, recent work suggests that ICs are EEG atoms with a well-defined focal origin that can be used to 'explain' their functional roles to the user [46]. The user can decide what information is transferred to the third parties, and can better understand what can be done with it. Multiple PDSes can also communicate with each other in order to calculate an aggregate answer to a question asked to a population, even further

⁶<http://www.brainresource.com/about-us/brain-resource-database>

increasing the user privacy.

Informed consent of the user to data sharing plays a crucial role in privacy implementation. As postulated in the Living Informed Consent concept, users should be empowered to understand and make informed decisions about access to their data [47]. The need for better consent procedure has been becoming a widely discussed issue in the biomedical research [48]. For the signal as complex as EEG, claiming that user understands the implications of sharing of the raw data is impossible. While the extraction of the high-level features, such as spectrograms or ICA components, limits the possible unauthorized uses of the data, it does not significantly change how informed is the user about potential abuses when granting the access. With access to massive EEG databases we can begin to estimate the effect of features sharing on the possibility of the user identification, providing this calculation before the sharing is executed. To further improve the understanding, we should aim for the calculation of the highest possible level of the answers in the user-controlled domain; rather than sharing spectrogram of the EEG data, user should share information whether she is epileptic or not. Only with such level of shared answers, the user can potentially understand the implications of sharing, both the positive and negative ones.

EEG data deserve our attention. The disclosure of the raw signal can be considered irreversible, as our brain activity remains relatively stable through the life [49] and we cannot replace our brain, at least for now. As the methods for data analysis and our general understanding of brain increases, recordings obtained once can be re-visited, providing new and unexpected insights. At the same time, EEG has become very accessible in terms of collection and analysis. Contrary to other well-established methods of recording brain activity, such as functional magnetic resonance imaging (fMRI) or magnetoencephalography (MEG), EEG can be feasibly used outside of the laboratory and operated by end-users [50]. Some of the uses of EEG are well understood and attractive for the users, such as accessible brain-computer interfaces (BCI) or neurofeedback applications. For those reasons, the EEG modality is arguably one of the most sensitive types of personal data that can still be captured in the privacy of home, or even on the go. Many approaches to sensitive personal data and medical data can be used in the context of EEG; it is important we start a discussion around using such practices in the evolving approaches to EEG data.

It is not a question if the databases of EEG data collected from large populations, for the purpose of providing services and building applications, will be created, but how soon. For this reason it is essential we begin a discussion around the privacy of EEG data, as seen and treated as personal data, available for public good, aligned with the vision of The New Deal on Data [51].

Architecture

Here we outline the architecture of combining the Smartphone Brain Scanner (SBS2) system with open Personal Data System (openPDS).

The Smartphone Brain Scanner [5] is an open-source system for collecting and processing EEG data from low-cost EEG systems using mobile devices. The framework has been successfully used to show the reconstruction of the neural sources from emotional stimulus [33], to implement BCI interaction, and build neurofeedback applications [50]. The hardware part of the system is based on the off-the-shelf consumer-grade neuroheadsets, such as Emotiv EEG, or custom-built mobile Emocap [52]. Various platforms and devices can be used for data collection, both mobile (Android) and desktop operating systems (OSX, Linux, Windows). Primarily used for recordings with mobile devices (smartphones or tablets), SBS2 is an example of advanced personal informatics systems, which can be used not only for research or medical purposes, but also by end-users. Full-blown applications can be built on top of the framework, both for data collection and analysis, as well as visualization and feedback. The recorded data are stored as binary files, containing raw EEG traces and additional metadata (timestamp, user, description, battery levels etc.).

The Personal Data System is a privacy-oriented framework for collection and sharing of personal data [6]. The particular implementations of the system, developed at MIT Media Lab Human Dy-

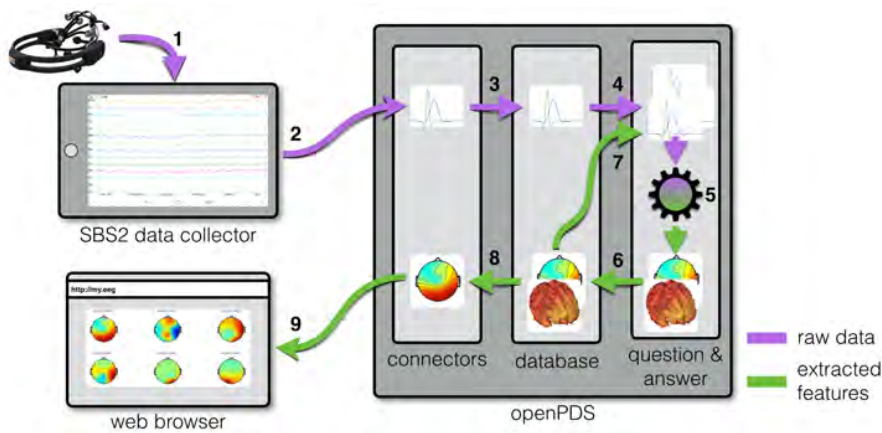


Figure 2. openPDS integration with Smartphone Brain Scanner. Raw EEG data are collected from neuroheadset on a mobile or stationary device (1) and uploaded to a server as a binary file (2). Data are then extracted and populated to a database (3). Periodic question & answer computation process operates on the raw data (4) extracting the high-level features of the data (5). The features are populated into the database in a form of high-level answers (6). Those answers can be used for the computation of other features (7). The pre-computed answers are accessed from the database (8) and served to the requesting application (9).

namics group and Technical University of Denmark, are known as openPDS. The primary feature of openPDS is computation of high-level answers based on raw data and sharing those with other services and applications, rather than exposing the raw data. Such low-dimensional answers are inherently more privacy-preserving, as they allow the user to better manage and understand what can happen with the shared data. When raw high-dimensional data are shared, many insights can be gained from them, for example raw GPS traces can be used to infer how much the user exercises, speeds when driving, or nocturnal schedule. In many cases, sharing such rich data is not required for the service to operate: To get the weather report for the city, users should not have to share their entire mobility trace.

We see the openPDS architecture as a suitable solution for the concerns in sharing personal EEG data. As described in the Introduction, the EEG data are extremely high-dimensional and can be used to identify users, diagnose mental disorders, or try to extract significant information directly from the recordings. For those reasons, the sharing of the raw EEG recordings should be as limited as possible. In the openPDS architecture, the raw data ideally never leave the user-controlled domain, and only the extracted features are shared, based on user authorizations. Originally created for personal data such as location, transaction records, friendship graphs, etc. the principles of openPDS become even more important in the context of brain activity recordings.

We present the outline of the architecture including SBS2 and openPDS in Figure 2. Raw data collected on mobile or stationary device (1) is uploaded to user-controlled openPDS (2) and stored in the database in the raw form (3). The assumption is that storing the raw data allows for multiple features to be extracted, with the possibility to install more questions in the future. The uploading application (data collector) has to be authorized by the user (in the OAuth2 sense) to be able to submit the data to

her PDS.

A periodic process calculates the answers from the raw data (4), using the algorithms installed by the services that access the data. The primary reason for periodic calculation of the answers is that those calculations are usually time-consuming and do not necessarily have to be strictly calculated on all the newest data. Having the answers readily available when they are requested, is often more important than having the exactly newest answer available. Nothing however prevents the computations to be performed when the answers are requested, provided such calculations are feasibly fast.

For the computation of the answers, both raw data and previously computed features can be used. The resulting answers are stored in the database, readily available for sharing with third parties, and to be used internally for other computations within the PDS. The answers are available as RESTful endpoints, protected by OAuth2 tokens, a solution based on standards common in many Internet-scale services [6]. Just as with many other Internet services, users can authorize third parties to access certain types of data (scopes) from the PDS. The applications accessing the data can live in the web-browser, on mobile devices, or as standalone programs.

The openPDS is not limited to storing only brain activity recordings of the user. Considering the EEG recordings as another personal data, that should be under the same user controls and shared in the same way, makes it easy to mash up the data from different sources. In a simple case, the additional data can be seen as metadata for the EEG recordings. For example, every time the user captures her brain activity, location can be saved and uploaded accordingly. An example answer that can be computed from such data is a list of places where user tends to get drowsy, without revealing the raw EEG recordings or the exact mobility traces. In more complex cases, where multiple types of data are collected, the EEG recordings become yet another data source that can be used for modeling of the user.

The solution presented here promotes the end-user control over sensitive data, at the same time making these data readily available for research purposes. Importantly, the architecture allows for privacy-preserving access to the data in real-time, making it possible to build services and applications on top of it. Additionally, the computations can be aggregated, in that the answers are computed from a group of PDSes, as presented in Figure 3. This can provide insights about the state of the population rather than individuals, potentially even more valuable for research purposes and privacy at the same time. Certain of those aggregation computations between PDSes can be performed in a privacy-preserving way, where no single entity learns the entire dataset. For example, collaborative filtering used in recommendation applications, can be done in a privacy-preserving way, where no information is leaked between the nodes participating in the computation [53]. Similarly, support vector machine (SVM) classification, one of the most popular classification methods for data mining and machine learning, can be performed under certain assumptions without disclosing the data of each party to others [54]. Comprehensive overviews of privacy-preserving machine learning methods is presented in [55] and [56]. It is outside of the scope of this article to investigate the particular solutions of the privacy-preserving machine learning, as those heavily depend on the application; here we signal the existence of the solutions potentially applicable for the widely-used treatment of EEG data.

OpenPDS for EEG data should offer several core features to effectively improve privacy controls. Primarily, openPDS needs to offer storage of structured data, accessible via API. The structure in the data is important for enabling the major feature of openPDS, computation of answers. OpenPDS is not a storage of unstructured data, like for example Dropbox, but offers execution of the calculations. Sharing of the calculated answers should be strongly preferred over sharing of the raw data; it may even be enforced that raw data is never shared and only sufficiently privacy-preserving features leave user-controlled system. The sharing of the data should be realized as a scalable service, based on user authorizations and using standards, such as OAuth2. All the flows of data should be realized through this API, without backdoor access: healthcare providers, health applications, or researchers all should use the same mechanism. The data access must be audited, so the user can monitor the data flows and either by manually accessing the logs or—preferably—by using tools automating the process by notifying only

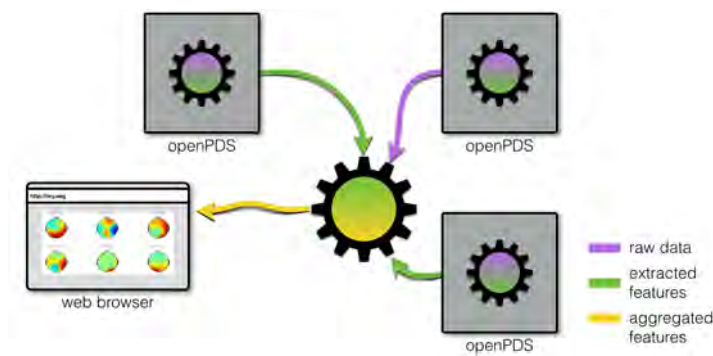


Figure 3. Group computation of answers from multiple PDSes. Depending on the nature of the computation, individual users’ PDSes can contribute raw data or extracted features, and aggregate answer is available to the calling service.

about unusual or suspicious data accesses. PDS implementation must be supported by a well-designed user interface, making the sharing and monitoring actions comprehensible for the end-user. Finally, the technical solutions of openPDS must be backed with aligned legal and business terms, supporting roles of the entities, their obligations, and allowed data flows.

Legal Framework

Brain activity datasets of the types described in this article pose especially important legal and policy issues. Personal data carry with them a wide variety of obligations and rights in general. The potential of neurological data to uniquely identify a person and to detect and convey psychological or other medical conditions raises particularly sensitive legal and public policy issues. The legal framework applicable to neurological data will determine which rules apply to these issues, and therefore what legal outcomes will occur. The relevant facts and circumstances surrounding the neurological data are the basis for establishing which legal frameworks are applicable.

Roles and Relationships

Whether a party is a data controller, a data holder, a data custodian, a data agent, a data receiver, or a data processor—to make but a few legal roles—will depend largely upon the underlying facts and circumstances of their particular involvement with brain activity data. Some parties will play combinations of various roles, and some parties will engage in just a few of the functions allocated to a given role, perhaps as an outsourced service provider the the party that is chiefly responsible in the role. From a technical perspective, each role carries with it a span of functions and expected interactions with other roles. From a legal perspective, each role has corresponding rights, obligation, and other applicable rules for the role.

The law can only be understood when it is factored into identified situations and contexts. One key facet of relevant context arises from the roles and relationships of any other individual or organization involved with the neurological data. Consider, for instance, a situation involving the measurement of

a patient's brain activity by their medical doctor. Clinical data used in a clinical context will likely invoke legal frameworks with detailed and prescriptive requirements about conduct like data collection, information security, and soliciting consent, such as Health Insurance Portability and Accountability Act (HIPAA) or Doctor/Patient Confidentiality. In such situations, other potentially applicable frameworks can include rules governing standards and quality of medical care (Malpractice) or limits on cost of service and billing practices (CMS Medicare/Medicaid) or even the contractual terms and intellectual property rights to information created as part of a medical encounter (patent).

It is difficult to conceive high stakes legal issues arising if no other person or organization has any role with or relationship to a given individual's creation, use, and deletion of their own neurological data. In theory, a purely and exclusively individual scenario of use can be imagined, assuming the brain activity equipment and the resulting neurological datasets are of, by, and for the same individual and no other party has any relationship, rights, responsibilities, role, or point of interaction interaction whatsoever. In this case, neither the raw data nor derived data would be shared or otherwise accessed by any other person and no basis for privacy issues would seem plausible.

By contrast, many potential legal frameworks may be triggered if that same individual provides the same neurological dataset to another legal entity. The legal obligations on the receiving party may vary based upon whether the individual was compelled to reveal, formally consented to provide, or informally choose to share their brain activity data. If duress or coercion compelled the data subject can invalidate consent and even undo contractual agreements. Furthermore, the rules may vary significantly depending on whether the individual disclosing their neurological data was under 18 years of age, e.g. [57], actively serving in the military [58, 59], was sleep walking at the time, had been lied to about the nature of the data⁷ or many, many other factors bearing on the capacity of the individual to make sound decisions about disclosure.

The roles may depend and change depending on the residence of the participant. For example, if the neurological data is of the brain activity of a resident of Massachusetts, additional roles may apply with a corresponding layer of relationships and information security obligations. The Massachusetts General Laws establish a statutory and regulatory scheme requiring service providers to encrypt personal information about a resident of the state, among other requirements (M.G.L. c. 93H, and 201 CMR 17.00). These rules apply when the brain activity data is associated with certain other personal information used to identify the user or as part of a billing relationship for a service (201 CMR 1702 Definitions: Personal information).

Under this Massachusetts legal framework for personal data information security, the key roles are (201 CMR 1702 Definitions: Service provider and Person):

- Service provider—any person that receives, stores, maintains, processes, or otherwise is permitted access to personal information through its provision of services directly to a person that is subject to this regulation
- Person—a natural person, corporation, association, partnership, or other legal entity, other than an agency, executive office, department, board, commission, bureau, division or authority of the Commonwealth, or any of its branches, or any political subdivision thereof

If the same data were held by a department or other unit of the state government, then the Massachusetts Fair Information Practices Act may apply yet a different layer of relationships and a range of respective duties and particular work flow for data access, record keeping and consent based sharing (M.G.L. c. 66A, informally known as FIPA⁸). The key rights and responsibilities are very similar to those proclaimed by the New Deal on Data [51] (see below), including a legislated right for people to be informed of the personal data about them held by the state, to be told of any third party access to that data and the purpose for that access, to request and receive a copy of the personal data about them,

⁷<http://www.ftc.gov/ftc-policy-statement-on-deception>

⁸<https://malegislature.gov/Laws/GeneralLaws/PartI/TitleX/Chapter66A>

and to ensure that data is not shared with other parties unless they personally consent to each such disclosure.

The key roles under the Massachusetts FIPA legal framework are:

- Agency—any agency of the executive branch of the government, including but not limited to any constitutional or other office, executive office, department, division, bureau, board, commission or committee thereof; or any authority created by the general court to serve a public purpose, having either statewide or local jurisdiction
- Data subject—an individual to whom personal data refers, not including corporations, corporate trusts, partnerships, limited partnerships, trusts, nor other similar entities
- Holder—an agency which collects, uses, maintains or disseminates personal data or any person or entity which contracts or has an arrangement with an agency whereby it holds personal data as part or as a result of performing a governmental or public function or purpose. A holder which is not an agency is a holder, and subject to the provisions of this chapter, only with respect to personal data so held under contract or arrangement with an agency

As will be discussed later in this section, the roles and duties of parties depend upon how personal data is defined in the context applicable to those parties. For instance, the definition of personal data under the Massachusetts FIPA law is:

any information concerning an individual which, because of name, identifying number, mark or description can be readily associated with a particular individual; provided, however, that such information is not contained in a public record, as defined in clause Twenty-sixth of section seven of chapter four and shall not include intelligence information, evaluative information or criminal offender record information as defined in section one hundred and sixty-seven of chapter six.

Whether information is contained in a public record or not does matter under this definition. The United States Supreme Court has indicated that public records relating to a person, when taken together from many different sources, may constitute in the aggregate a violation of privacy rights. Under this standard, despite the public record status of data, it is possible that it will nonetheless be deemed to be personal data under the law. Therefore, whether a given party is or is not in the role of a personal data holder does depend upon how personal data is currently defined in a given context. Parties that generate, receive, store, analyze, and share brain activity data are likely to exist in several contexts and therefore to hold a variety of roles with respect to that personal data.

Clarity is needed regarding the role of the parties initially engaged in the provision and use or hosting of brain activity obtained with consumer level equipment and data storage enabling individuals to generate and use such data about themselves. The relationship between the individual data subject and the company or companies providing the equipment and services needed to create and use brain activity data in an individual or small group consumer context will determine the legal results and privacy rights, responsibilities, and other rules. The role and relationships between individuals and providers of personal neurological equipment and services can be found in the contracts and other agreements between those parties. The terms of service, privacy policy, and other such agreements literally and explicitly define and describe the roles and obligations of each party vis-a-vis each other party. Industry practices, standards and common approaches are needed to ensure widely understood terms and conditions are consistently applied. While statutes and regulations can provide further certainty about the legal roles and relationships of parties to brain activity data, the use of common and agreed contractual terms is a more agile and adaptable method.

Reasonable Expectation

Parties who play a role in the use of brain activity data must respect privacy interests of the data subject. But defining the appropriate individual rights and obligations allocated to each role depends on the privacy and related frameworks applicable to those roles. Fundamentally, the law reflects agreed or at least widely understood expectations about behaviors and consequences. Some statutes explicitly base a rule on whether a behavior would be considered an “unreasonable” interference with a right under all the relevant circumstances. For instance, state law of the Commonwealth of Massachusetts provides: “A person shall have a right against unreasonable, substantial or serious interference with his privacy” (MGL Ch214 Sec1b). However, precisely what behavior or situations are deemed reasonable or unreasonable are deliberately left to adjudication on a case by case basis. Naturally, as cultural, social, political, and other norms change, the line between permitted legal conduct and prohibited privacy violations will change correspondingly.

The trends toward open data, quantified self, and social networking are gaining momentum. These changing attitudes and practices are also moving the set-point for what types of conduct might be reasonably agreed to be privacy violations.

The New Deal on Data

There are many existing legal frameworks covering personal data. The novelty and quickly evolving nature of products, services, and use cases centered upon personally created and used neurological readings presents unprecedented factual contexts and therefore yields uncertainty about the applicable rules. For this reason, and also in order to ensure the value of these creative technologies remains available and grows, it is important to establish a sound and predictable legal framework applicable to personal neurological data and surrounding practices.

The New Deal on Data [51] provides a simple, efficient and effective approach for establishing the legal framework for personal neuroinformatics. The New Deal on Data is a refined and focused statement of the most fundamental facets of the fair information practices:

1. You have a right to possess your data. Companies should adopt the role of a bank account for your data, where you open an account (anonymously, if possible), and you can remove your data whenever you like.
2. You, the data owner, must have full control over the use of your data. If you are not happy with the way a company uses your data, you can remove it. All of it. Everything must be opt-in, and not only clearly explained in plain language, but with regular reminders about the status.
3. You have a right to dispose or distribute your data. If you want to destroy it or remove it and redeploy it elsewhere, you have the right to do it.

The Overarching Evolving International Legal Framework

The 2013 Organization for Economic Co-operation and Development (OECD) Privacy Guidelines⁹ represent the first revision to the OECD fair information practices since they were initially agreed internationally in 1980.

An important aspect of these Guidelines is their focus on obligations of those who are Data Controllers meaning “a party who, according to national law, is competent to decide about the contents and use of personal data regardless of whether or not such data are collected, stored, processed or disseminated by that party or by an agent on its behalf”. The Data Controller is obliged to protect Personal Data under their control, and such data is defined as “any information relating to an identified or identifiable

⁹<http://www.oecd.org/sti/ieconomy/2013-oecd-privacy-guidelines.pdf>

individual (data subject)”. This includes an obligation to keep personal data secure and correct and to provide, upon the request, an individual with a copy of the personal data about them. These guidelines are intended to apply to both public sector and private sector Data Controllers.

A major update to the OECD Privacy Guidelines includes some clear signals about top priority legal and policy reforms that are highly relevant to neurological personal data. Two of the most important topics identified in the updated text are:

1. Biologically based human information, including biometric and genomic data and how this bio-info is an important emerging class of personal data with unique legal implications.
2. Big Data and statistical models, including predictive analytics as a harbinger of a very different playing field for privacy and broadly held expectations about the nature and purposes of personal data flows.

Regarding “the human body as information” the 2013 OECD Guidelines note:

Advances in genetic technology have important implications for the health of individuals, helping researchers better understand, prevent and treat various diseases. Genetic testing to assess health risks or to determine biological relationships raises issues that affect not only an individual's privacy but also raise the issue of ‘group privacy’, as our genetic makeup is shared by other members of our family and community. At the same time the indelible nature of genetic information and its potential implications for discriminatory treatment make it particularly sensitive.

Commonly viewed as a means of identification and authentication, biometrical information is beginning to be collected and used in a greater variety of contexts—from voice recognition systems for allowing employees to access business applications to digital fingerprinting to pay for lunch at an elementary school. As technology advances, the use of additional human characteristics as information will continue to pose challenges to notions of privacy and dignity. The reliability of biometric information and systems has improved, and biometrics are generally considered strong and valuable to authentication systems. The question of whether biometrics invades privacy or protects it, or both, as well as the appropriateness of relying on biometrics to resolve problems or make decisions about individuals, will be issues that will need to be considered as biometric technologies evolve.

The direction of a policy and legal direction in alignment with the principles of the New Deal on Data is even clearer when the commentary regarding human biological data is read in the context of global trends toward adoption of and reliance on Big Data and data-driven services and lines of business. In relevant part, the 2013 OECD Guidelines observe:

The development and use of algorithms and analytics has made large data sets more accessible and capable of being linked, which can result in increased and new uses of the data, thereby making data more valuable. The remarkable pace of development and evolution of technologies and business models make it less easy to accurately describe potential future uses of information at the time of collection. This has resulted in a desire to keep personal data for an as-yet undefined, later purpose and reflects the intrinsic value of personal data to both business and governments. Search engines, which allow for easy, global searches of any personal data made public, make data retrieval much easier for Internet users. Growing use of linked data sources and contextual semantic technologies allow for greater and more sophisticated automation in the discovery and aggregation of personal data. Automated decision-making through data mining and rule engines is increasingly possible in a variety of contexts. Moreover, searches are no longer restricted to text and numbers: facial recognition applications now allow users to

identify individuals in images online with growing accuracy. The phenomenon of “big data”, namely, the vast quantities of data that can be stored, linked, and analysed, brings with it the possibility of finding information, trends, insights that were not previously obvious or capable of being ascertained. This may hold great economic and social value, but there can be privacy implications.

Understanding the role of every party to the creation, use, access, modification, sharing, and destruction of brain activity data is key to applying an acceptable legal framework. If the commercial company providing consumer equipment and services needed to collect personal data brain activity is considered a Data Controller in the OECD Privacy Guidelines sense, then a New Deal on Data will follow for down stream uses and contexts. However, if such providers are considered eCommerce-like owners of services and data systems in the model of today, then very different legal outcomes will likely follow. Whether individuals are an immediate and continuing role as owners or at least key control points over their brain activity is essentially a question of which legal framework roles and relationships will be applied.

In the aftermath of major defining security failures, from the Snowden disclosures to the Target breach to name only two, there appears to be a rare opportunity for deeper and broader legal and policy reform than has been witnessed in many years. Many US state legislatures are debating statutes that would prevent and/or severely punish personal data abuses while the EU is increasing pressure to repeal the long-standing “Safe Harbor” agreements for trans-Atlantic personal data flows in response to the evident lack of personal data stewardship on the Western edge of the partnership. The National Strategy for Trusted Identity in Cyberspace (NSTIC) Identity Ecosystem Steering Group (IDESG) is one example of a potential avenue for fresh thinking from a shared set of basic values founded on the Fair Information Practice Principles. This type of multi-stakeholder forum on personal data standard and policy framework could validly develop, credibly propose, and provide continuing support for New Deal on Data oriented identity data frameworks.

Discussion

In the biomedical field, there is a growing discussion about how informed consent and data sharing practices are in need of serious improvement [48, 60]. It would be irresponsible to continue collection of data of higher and higher resolution, from growing number of participants, over long periods of time without the discussion about how to provide better privacy guarantees. This is especially true for the biomedical data, that change little in persons’ lifetime and once acquired by malicious parties can do significant harm for a long time.

The main goal of building privacy-preserving services for personal data is not to hide the data or to make them unavailable; quite the opposite. We need more data sharing for the public good, EEG recordings are no exception. Implementation of end-user control over the data is a way of increasing data liquidity, allowing for more organized and better managed flows. With cheap recording devices and online services able to generate value for the end-user, for the first time in the history we can start looking at the brain activity of the entire populations. It is however important that such data will not become exclusive to commercial services, closed in silos unavailable for large-scale research. Implementation of the architectures such as one outlined here is a way to promote data availability while protecting the users contributing these data. This is well aligned with the concept of the New Deal on Data [51], postulating increased availability of the personal data driven by end-user data ownership.

We postulate the data ownership should be given to the user, at the same time recognizing that the EEG data is extremely complex; even short recordings can be useful for many purposes. The only sensible way to increase the data availability while protecting the privacy of the users is with the question & answer mechanism. Very significant portions of the calculations must happen under user control, when only extracted features are shared with the third parties; features that make it possible to understand

what knowledge can be extracted from them. The technical solution of question & answer will not be perfect. Even when sharing very high-level features, there are still dangers of abuse: multiple answers can be combined, sensitive answers can be shared without user authorization, new analysis methods can allow for reuse of the shared features. Researching how to limit those on the technical grounds, for example by monitoring how the requested answers cover the original signal, is important but not sufficient. The legal framework, including contract governance, credible threat of legal consequences, and robust auditing system need to be integrated in the systems. At the end of the day, if there is money to be made from the data abuse, technical means will be defeated by motivated attacker and only legal framework can limit a widespread abuse.

Significantly more research about the sensitivity of the EEG data is urgently needed. If I post a minute of my raw EEG data on Facebook today, will I become indefinitely identifiable in every subsequent EEG database? Will the researchers of tomorrow be able to learn about my mental diseases? Without even rough answer to those questions, it is very hard to discuss and implement best practices for handling personal EEG data.

As we build online services for collection and analysis for EEG data and deploy research studies with unprecedented capabilities of EEG recording, very novel value will be available for service providers, researchers, and users. For example, in Figure 4 we show a mockup of a service showing geo-tagged results from brain scans. Shown frequencies, 4 and 14 Hz have been associated with drowsiness level [61], and such map could be a service for plotting the engaging places in the city. Or, if applied to scans performed while driving a car, a live monitoring tool for mapping places and times, where the drivers become dangerously drowsy. Such services can be possible with the development of 24/7 EEG recording methods, for example low-dimensionality neuroheadsets, subcutaneously placed electrodes [62], or electrodes placed in the ear canal [63]. Researchers and service providers in openPDS architecture may only access aggregate data from multiple users, averaged over time, and only certain features.



Figure 4. Mockup of a service showing geo-tagged brain activity frequencies. Frequencies displayed are recorded by users using personal neuroinformatics system, such as Smartphone Brain Scanner, and associated with location data. Researchers may access view aggregated over multiple users and time, whereas users can see their own data exactly.

Services collecting and processing massive biomedical and health data—including EEG—should adapt the openPDS approach, offering to the user hosting of their data, with the understanding that users can control the data access authorizations, request deletion of the data, or move the data to another

service provider. Clear boundaries within those services should be set, defining in business, legal, and technical aspects what is under user control and what extracted high-level answers are used for providing the services. Business model of collecting large datasets from the users in exchange for a service, and subsequent selling access to those datasets to the researchers is arguably a dangerous model in a context where the sensitivity, value, and proper anonymization techniques are not sufficiently researched. It would be a broken economy.

Here we presented an outline of a solution, one way of providing privacy for personal neuroinformatics. Many questions still need be asked and answered. What are the precise legal frameworks for treating high-resolution biomedical data as personal data. What are the features and answers that can be considered safe to share. Are ICA components such answers? Source reconstructions of the activity? Spectrograms? What can be used to identify the users and how well, or what unexpected findings can be computed?

We hope to invite the neuroscience and EEG communities to discuss the privacy and liquidity of the data, as seen in the context of online service and massive research studies. The time of personal neuroinformatics is coming, and such discussion is necessary before we end up with extremely sensitive data floating around wildly. Fixing this a posteriori may be difficult, if not impossible. We should own our brain activity, an extremely valuable and sensitive asset that we should have the right to contribute for the public good.

References

1. Jung R, Berger W (1979) Fiftieth anniversary of hans berger's publication of the electroencephalogram. his first records in 1924–1931 (author's transl)]. *Archiv für Psychiatrie und Nervenkrankheiten* 227: 279.
2. Carskadon MA, Rechtschaffen A (2000) Monitoring and staging human sleep. *Principles and practice of sleep medicine* 3: 1197–1215.
3. Poline JB, Breeze JL, Ghosh S, Gorgolewski K, Halchenko YO, et al. (2012) Data sharing in neuroimaging research. *Frontiers in neuroinformatics* 6.
4. Metzger MJ, Flanagan AJ (2011) Using web 2.0 technologies to enhance evidence-based medical information. *Journal of health communication* 16: 45–58.
5. Stopczynski A, Larsen JE, Stahlhut C, Petersen MK, Hansen LK (2011) A smartphone interface for a wireless eeg headset with real-time 3d reconstruction. In: *Affective Computing and Intelligent Interaction*, Springer. pp. 317–318.
6. de Montjoye YA, Wang SS, Pentland A, Anh DTT, Datta A, et al. (2012) On the trusted use of large-scale personal data. *IEEE Data Eng Bull* 35: 5–8.
7. Labrecque LI, Markos E, Milne GR (2011) Online personal branding: processes, challenges, and implications. *Journal of Interactive Marketing* 25: 37–50.
8. Kosinski M, Stillwell D, Graepel T (2013) Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences* 110: 5802–5805.
9. Stopczynski A, Stahlhut C, Larsen JE, Petersen MK, Hansen LK (2014) The smartphone brain scanner: A portable real-time neuroimaging system. *PloS one* 9: e86733.
10. Blankertz B, Dornhege G, Krauledat M, Müller KR, Curio G (2007) The non-invasive berlin brain-computer interface: fast acquisition of effective performance in untrained subjects. *NeuroImage* 37: 539–550.

11. Simanova I, van Gerven M, Oostenveld R, Hagoort P (2010) Identifying object categories from event-related eeg: toward decoding of conceptual representations. *PloS one* 5: e14465.
12. Karson CN, Coppola R, Daniel DG, Weinberger DR (1988) Computerized eeg in schizophrenia. *Schizophrenia bulletin* 14: 193.
13. Sponheim SR, Clementz BA, Iacono WG, Beiser M (1994) Resting eeg in first-episode and chronic schizophrenia. *Psychophysiology* 31: 37–43.
14. Dauwels J, Vialatte F, Musha T, Cichocki A (2010) A comparative study of synchrony measures for the early diagnosis of alzheimer's disease based on eeg. *NeuroImage* 49: 668–693.
15. Gotlib IH (1998) Eeg alpha asymmetry, depression, and cognitive functioning. *Cognition & Emotion* 12: 449–478.
16. Davidson RJ, Pizzagalli D, Nitschke JB, Putnam K (2002) Depression: perspectives from affective neuroscience. *Annual review of psychology* 53: 545–574.
17. Smith S (2005) Eeg in the diagnosis, classification, and management of patients with epilepsy. *Journal of Neurology, Neurosurgery & Psychiatry* 76: ii2–ii7.
18. Lantz G, Grave de Peralta R, Spinelli L, Seeck M, Michel C (2003) Epileptic source localization with high density eeg: how many electrodes are needed? *Clinical Neurophysiology* 114: 63–69.
19. Rubin MN, Jeffery OJ, Fugate JE, Britton JW, Cascino GD, et al. (2014) Efficacy of a reduced electroencephalography electrode array for detection of seizures. *The Neurohospitalist* 4: 6–8.
20. Revett K, de Magalhães ST (2010) Cognitive biometrics: Challenges for the future. In: *Global Security, Safety, and Sustainability*, Springer. pp. 79–86.
21. Poulos M, Rangoussi M, Alexandris N (1999) Neural network based person identification using eeg features. In: *Acoustics, Speech, and Signal Processing, 1999. Proceedings., 1999 IEEE International Conference on. IEEE*, volume 2, pp. 1117–1120.
22. Paranjape R, Mahovsky J, Benedicenti L, Koles Z (2001) The electroencephalogram as a biometric. In: *Electrical and Computer Engineering, 2001. Canadian Conference on. IEEE*, volume 2, pp. 1363–1366.
23. Marcel S, Millán JdR (2007) Person authentication using brainwaves (eeg) and maximum a posteriori model adaptation. *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 29: 743–752.
24. De Gennaro L, Marzano C, Fratello F, Moroni F, Pellicciari MC, et al. (2008) The electroencephalographic fingerprint of sleep is genetically determined: a twin study. *Annals of neurology* 64: 455–460.
25. Finelli LA, Achermann P, Borbély AA (2001) Individual fingerprints in human sleep eeg topography. *Neuropsychopharmacology* 25: S57–S62.
26. de Montjoye YA, Hidalgo CA, Verleysen M, Blondel VD (2013) Unique in the crowd: The privacy bounds of human mobility. *Scientific reports* 3.
27. Sweeney L (2000) Simple demographics often identify people uniquely. *Health (San Francisco)* : 1–34.

28. Martinovic I, Davies D, Frank M, Perito D, Ros T, et al. (2012) On the feasibility of side-channel attacks with brain-computer interfaces. In: 21st USENIX Security Symp.
29. Abootalebi V, Moradi MH, Khalilzadeh MA (2009) A new approach for eeg feature extraction in p300-based lie detection. *Computer methods and programs in biomedicine* 94: 48–57.
30. Rosenfeld JP, Biroshak JR, Furedy JJ (2006) P300-based detection of concealed autobiographical versus incidentally acquired information in target and non-target paradigms. *International Journal of Psychophysiology* 60: 251–259.
31. Frank M, Hwu T, Jain S, Knight R, Martinovic I, et al. (2013) Subliminal probing for private information via eeg-based bci devices. *arXiv preprint arXiv:13126052*.
32. Pulvermüller F (2012) Meaning and the brain: The neurosemantics of referential, interactive, and combinatorial knowledge. *Journal of Neurolinguistics* 25: 423–459.
33. Petersen MK, Stahlhut C, Stopczynski A, Larsen JE, Hansen LK (2011) Smartphones get emotional: mind reading images and reconstructing the neural sources. In: *Affective Computing and Intelligent Interaction*, Springer. pp. 578–587.
34. Tran Y, Craig A, Boord P, Connell K, Cooper N, et al. (2006) Personality traits and its association with resting regional brain activity. *International journal of psychophysiology* 60: 215–224.
35. <http://neuro.compute.dtu.dk/wiki/Electroencephalography#Data>. [Online; accessed 2013-11-29].
36. http://sccn.ucsd.edu/arno/fam2data/publicly_available_EEG_data.html. [Online; accessed 2013-11-29].
37. http://emotivinsight.com/upload/press_release/Emotiv1MAnnouncementPressRelease.pdf. [Online; accessed 2013-11-29].
38. Shambroom JR, Fabregas SE, Johnstone J (2012) Validation of an automated wireless system to monitor sleep in healthy adults. *Journal of Sleep Research* 21: 221–230.
39. Chaudhuri K, Sarwate AD (2013) A near-optimal algorithm for differentially-private principal components. *Journal of Machine Learning Research* 14: 2905–2943.
40. Gordon E, Cooper N, Rennie C, Hermens D, Williams L (2005) Integrative neuroscience: the role of a standardized database. *Clinical EEG and Neuroscience* 36: 64–75.
41. Hunter M, Smith R, Hyslop W, Rosso O, Gerlach R, et al. (2005) The australian eeg database. *Clinical EEG and neuroscience* 36: 76–81.
42. Mørup M, Hansen LK, Herrmann CS, Parnas J, Arnfred SM (2006) Parallel factor analysis as an exploratory tool for wavelet transformed event-related eeg. *NeuroImage* 29: 938–947.
43. Mørup M, Hansen LK, Arnfred SM, Lim LH, Madsen KH (2008) Shift-invariant multilinear decomposition of neuroimaging data. *NeuroImage* 42: 1439–1450.
44. Eckersley P, Egan GF, De Schutter E, Yiyuan T, Novak M, et al. (2003) Neuroscience data and tool sharing. *Neuroinformatics* 1: 149–165.
45. Onton J, Westerfield M, Townsend J, Makeig S (2006) Imaging human eeg dynamics using independent component analysis. *Neuroscience & Biobehavioral Reviews* 30: 808–822.

46. Delorme A, Palmer J, Onton J, Oostenveld R, Makeig S (2012) Independent eeg sources are dipolar. *PLoS one* 7: e30135.
47. Pietri R (2013). Privacy in computational social science. URL <http://www.compute.dtu.dk/English.aspx>. DTU supervisor: Sune Lehmann Jørgensen, sljo@dtu.dk, DTU Compute.
48. (2012). "time to open up". doi:doi:10.1038/486293a. URL <http://www.nature.com/nature/journal/v486/n7403/full/486293a.html>.
49. Dustman R, Shearer D, Emmerson R (1999) Life-span changes in eeg spectral amplitude, amplitude variability and mean frequency. *Clinical neurophysiology* 110: 1399–1409.
50. Stopczynski A, Stahlhut C, Petersen MK, Larsen JE, Jensen CF, et al. (2013) Smartphones as pocketable labs: Visions for mobile brain imaging and neurofeedback. *International Journal of Psychophysiology* : <http://dx.doi.org/10.1016/j.ijpsycho.2013.08.007>.
51. Pentland A (2009) Reality mining of mobile communications: Toward a new deal on data. *The Global Information Technology Report 2008–2009* : 1981.
52. Debener S, Minow F, Emkes R, Gandras K, Vos M (2012) How about taking a low-cost, small, and wireless eeg for a walk? *Psychophysiology* 49: 1617–1621.
53. Canny J (2002) Collaborative filtering with privacy. In: *Security and Privacy, 2002. Proceedings. 2002 IEEE Symposium on*. IEEE, pp. 45–57.
54. Yu H, Jiang X, Vaidya J (2006) Privacy-preserving svm using nonlinear kernels on horizontally partitioned data. In: *Proceedings of the 2006 ACM symposium on Applied computing*. ACM, pp. 603–610.
55. Agrawal R, Srikant R (2000) Privacy-preserving data mining. In: *ACM Sigmod Record*. ACM, volume 29, pp. 439–450.
56. Aggarwal CC, Philip SY (2008) *A general survey of privacy-preserving data mining models and algorithms*. Springer.
57. (1991). Age of legal capacity (scotland) act 1991. <http://www.legislation.gov.uk/ukpga/1991/50/enacted>.
58. Uniform code of military justice. <http://www.au.af.mil/au/awc/awcgate/ucmj.htm>.
59. Geneva conventions: 1949 conventions and additional protocols, and their commentaries. <http://www.icrc.org/applic/ihl/ihl.nsf/vwTreaties1949.xsp>.
60. Hayden EC (2012). "informed consent: A broken contract". URL <http://www.nature.com/news/informed-consent-a-broken-contract-1.10862>.
61. Jung TP, Makeig S, Stensmo M, Sejnowski TJ (1997) Estimating alertness from the eeg power spectrum. *Biomedical Engineering, IEEE Transactions on* 44: 60–69.
62. Beck-nielsen H (2007). Method and apparatus for prediction and warning of hypoglycaemic attack. EP Patent 1,827,209.
63. Looney D, Kidmose P, Park C, Ungstrup M, Rank ML, et al. (2012) The in-the-ear recording concept: User-centered and wearable brain monitoring. *Pulse, IEEE* 3: 32–42.

Bibliography

- [ABK09] S. Avancha, A. Baxi, and D. Kotz. Privacy in mobile technology for personal healthcare. *Submitted to ACM Computing Surveys*, 2009.
- [ACG⁺03] Patricia Agre, Frances A Campbell, Barbara D Goldman, Maria L Boccia, Nancy Kass, Laurence B McCullough, Jon F Merz, Suzanne M Miller, Jim Mintz, Bruce Rapkin, et al. Improving informed consent: the medium is not the message. *IRB: Ethics and Human Research*, 25(5):S11–S19, 2003.
- [AHJ12] Minkyu Ahn, Jun Hee Hong, and Sung Chan Jun. Feasibility of approaches combining sensor and source features in brain-computer interface. *Journal of Neuroscience Methods*, 204:168–178, 2012.
- [AKP12] Hubertus Axer, Carsten M. Klingner, and Andreas Prescher. Fiber anatomy of dorsal and ventral language streams. *Brain & Language*, <http://dx.doi.org/10.1016/j.bandl.2012.04.015>, 2012.
- [AN10] I. Aad and V. Niemi. Nrc data collection and the privacy by design principles. *Proc. of PhoneSense*, pages 41–45, 2010.
- [API⁺11] N. Aharony, W. Pan, C. Ip, I. Khayal, and A. Pentland. Social fmri: Investigating and shaping social mechanisms in the real world. *Pervasive and Mobile Computing*, 2011.
- [AW12] Sinan Aral and Dylan Walker. Identifying influential and susceptible members of social networks. *Science*, 337(6092):337–341, 2012.
- [Bal07] Ran D Balicer. Modeling infectious diseases dissemination through online role-playing games. *Epidemiology*, 18(2):260–261, 2007.
- [BALP01] Jessica W Berg, Paul S Appelbaum, Charles W Lidz, and Lisa S Parker. Informed consent: legal theory and clinical practice. 2001.
- [BCL⁺00] F. Babiloni, F. Cincotti, L. Lazzarini, J. Millan, J. Mourino, M. Varsta, J. Heikkinen, L. Bianchi, and MG Marciani. Linear classification of low-resolution eeg patterns produced by imagined hand movements. *Rehabilitation Engineering, IEEE Transactions on*, 8(2):186–188, 2000.
- [BDK⁺06] B. Blankertz, G. Dornhege, M. Krauledat, K.R. Muller, V. Kunzmann, F. Losch, and G. Curio. The berlin brain-computer interface: Eeg-based communication without subject training. *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, 14(2):147–152, 2006.

- [BG97] S. Baillet and L. Garnero. A bayesian approach to introducing anatomo-functional priors in the EEG/MEG inverse problem. *IEEE Trans. Biomed. Eng.*, 44:374–385, 1997.
- [Bis13] Mina Bissell. Reproducibility: The risks of the replication drive. *Nature*, 503:333–334, 2013.
- [BK10] R. Böhme and S. Köpsell. Trained to accept?: A field experiment on consent dialogs. In *Proceedings of the 28th international conference on Human factors in computing systems*, pages 2403–2406. ACM, 2010.
- [BMG11] Michel Besserve, Jacques Martinerie, and Line Garnero. Improving quantification of functional networks with eeg inverse problem: Evidence from a decoding point of view. *NeuroImage*, 55(4):1536–1547, 2011.
- [BML01] S. Baillet, J.C. Mosher, and R.M. Leahy. Electromagnetic brain mapping. *IEEE Signal Processing Magazine*, 18:14–30, 2001.
- [BP11] P Ashok Babu and KVSVR Prasad. Removal of ocular artifacts from eeg signals using adaptive threshold pca and wavelet transforms. In *Communication Systems and Network Technologies (CSNT), 2011 International Conference on*, pages 572–575. IEEE, 2011.
- [BRS11] Barry Brown, Stuart Reeves, and Scott Sherwood. Into the wild: challenges and opportunities for field trial methods. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 1657–1666. ACM, 2011.
- [BTV⁺10] B. Blankertz, M. Tangermann, C. Vidaurre, S. Fazli, C. Sannelli, S. Haufe, C. Maeder, L. Ramsey, I. Sturm, G. Curio, et al. The berlin brain-computer interface: non-medical uses of bci technology. *Frontiers in Neuroscience*, 4, 2010.
- [BZ04] Andreas Bartels and Semir Zeki. Functional brain mapping during free viewing of natural scenes. *Human brain mapping*, 21(2):75–85, 2004.
- [CF09] N.A. Christakis and J.H. Fowler. *Connected: The Surprising Power of Our Social Networks and How They Shape Our Lives*. Little, Brown and Company, 2009.
- [CHLD99] RQ Cui, D Huter, W Lang, and L Deecke. Neuroimage of voluntary movement: topography of the bereitschaftspotential, a 64-channel dc current source density study. *Neuroimage*, 9(1):124–134, 1999.
- [CLL06] M. Congedo, F. Lotte, and A. Lécuyer. Classification of movement intention by spatially filtered electromagnetic inverse solutions. *Physics in Medicine and Biology*, 51:1971–1989, 2006.
- [CP03] T. Choudhury and A. Pentland. Sensing and modeling human networks using the sociometer. In *Proc. the 7th IEEE International Symposium on Wearable Computers (ISWC2003)*, pages 216–222, 2003.
- [CPC03] John A. Caldwell, Brian Przinko, and J. Lynn Caldwell. Body posture affects electroencephalographic activity and psychomotor vigilance task performance in sleep-deprived subjects. *Clinical Neurophysiology*, 114:23–31, 2003.
- [CSB⁺00] Bruce N Cuthbert, Harald T Schupp, Margaret M Bradley, Niels Birbaumer, and Peter J Lang. Brain potentials in affective picture processing: covariation with autonomic arousal and affective report. *Biological psychology*, 52(2):95–111, 2000.
- [CZSSM80] Barrie R Cassileth, Robert V Zupkis, Katherine Sutton-Smith, and Vicki March. Informed consent—why are its goals imperfectly realized? *The New England journal of medicine*, 302(16):896–900, 1980.
- [DB02] Zoltán Dezső and Albert-László Barabási. Halting viruses in scale-free networks. *Physical Review E*, 65(5):055103, 2002.

- [DBCM04] G. Dornhege, B. Blankertz, G. Curio, and K.R. Müller. Boosting bit rates in non-invasive EEG single-trial classifications by feature combination and multi-class paradigms. *IEEE Trans. Biomed. Eng.*, 51(6):993–1002, 2004.
- [DDWB13] Gavin J Dollman, Lizette De Wet, and Tanya R Beelders. Effectiveness with eeg bcis: exposure to traditional input methods as a factor of performance. In *Proceedings of the South African Institute for Computer Scientists and Information Technologists Conference*, pages 77–80. ACM, 2013.
- [DLP+02] Laura B Dunn, Laurie A Lindamer, Barton W Palmer, Shahrokh Golshan, Lawrence J Schneiderman, and Dilip V Jeste. Improving understanding of research consent in middle-aged and elderly patients with psychotic disorders. *The American journal of geriatric psychiatry*, 10(2):142–150, 2002.
- [DME+12] S. Debener, F. Minow, R. Emkes, K. Gandras, and M. Vos. How about taking a low-cost, small, and wireless eeg for a walk? *Psychophysiology*, 2012.
- [dMSS+14] Y.A. de Montjoye, A. Stopczynski, E. Shmueli, A. Pentland, and S. Lehmann. The strength of the strongest ties in collaborative problem solving. *Scientific Reports*, Submitted (2014).
- [dMWP12] Yves-Alexandre de Montjoye, Samuel S Wang, and Alex Pentland. On the trusted use of large-scale personal data. *IEEE Data Eng. Bull.*, 35(4):5–8, 2012.
- [Dru09] Dr. Chris Drummond. Replicability is not reproducibility: Nor is it good science. June 2009.
- [DSDP12] Jacek P Dmochowski, Paul Sajda, Joao Dias, and Lucas C Parra. Correlated components of ongoing eeg point to emotionally laden attention—a possible marker of engagement? *Frontiers in human neuroscience*, 6, 2012.
- [DSM07] Arnaud Delorme, Terrence J. Sejnowski, and Scott Makeig. Enhanced detection of artifacts from eeg data using higher-order statistics and independent component analysis. *NeuroImage*, 34(4), 2007.
- [DVGD13] Maarten De Vos, Katharina Gandras, and Stefan Debener. Towards a truly mobile auditory brain–computer interface: Exploring the p300 to take away. *International Journal of Psychophysiology*, 2013.
- [DWD+09] F. Drechsler, CH Wolters, T. Dierkes, H. Si, and L. Grasedyck. A full subtraction approach for finite element method based source analysis using constrained Delaunay tetrahedralisation. *NeuroImage*, 46(4):1055–1065, 2009.
- [EFW12] S. Egelman, A.P. Felt, and D. Wagner. Choice architecture and smartphone privacy: There’s a price for that. In *Workshop on the Economics of Information Security (WEIS)*, 2012.
- [EP06] N. Eagle and A. Pentland. Reality mining: sensing complex social systems. *Personal and Ubiquitous Computing*, 10(4):255–268, 2006.
- [Eri88] K Jeffrey Eriksen. Non-distorting post-acquisition line-frequency filter for evoked potentials. In *Engineering in Medicine and Biology Society, 1988. Proceedings of the Annual International Conference of the IEEE*, pages 1168–vol. IEEE, 1988.
- [EZG04] Tobias Egner, T. F. Zech, and John H Gruzelier. The effects of neurofeedback training on the spectral topography of the electroencephalogram. *Clinical Neurophysiology*, 115(11):2452–2460, November 2004.
- [FBL+03] Thomas Fuchs, Niels Birbaumer, Werner Lutzenberger, John H Gruzelier, and Jochen Kaiser. Neurofeedback treatment for attention-deficit/hyperactivity disorder in children: a comparison with methylphenidate. *Applied psychophysiology and biofeedback*, 28(1):1–12, March 2003.

- [FC08] J.H. Fowler and N.A. Christakis. Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the framingham heart study. *British Medical Journal*, 337:a2338, 2008.
- [FGW11] A.P. Felt, K. Greenwood, and D. Wagner. The effectiveness of application permissions. In *Proc. of the USENIX Conference on Web Application Development*, 2011.
- [FLM05] B. Friedman, P. Lin, and J.K. Miller. Informed consent by design. *Security and Usability*, pages 495–521, 2005.
- [FMM⁺97] Ian Fureman, Kathleen Meyers, A Thomas McLellan, David Metzger, and George Woody. Evaluation of a video-supplement to informed consent: injection drug users and preventive hiv vaccine efficacy trials. *AIDS education and prevention: official publication of the International Society for AIDS Education*, 9(4):330–341, 1997.
- [FS11] John J. Foxe and Adam C. Snyder. The role of alpha-band brain oscillations as a sensory suppression mechanism during selective attention. *Frontiers in Psychology*, 2(doi: 10.3389/fpsyg.2011.00154):1–13, July 2011.
- [FSAF13] Bertalan Forstner, Luca Szegletes, Robert Angeli, and Andras Fekete. A general framework for innovative mobile biofeedback based educational games. In *Cognitive Infocommunications (CogInfoCom), 2013 IEEE 4th International Conference on*, pages 775–778. IEEE, 2013.
- [GFFR96] Vittorio Gallese, Luciano Fadiga, Leonardo Fogassi, and Giacomo Rizzolati. Action recognition in the premotor cortex. *Brain*, 119:593–609, 1996.
- [GGF⁺11] K. Gramann, J.T. Gwin, D.P. Ferris, K. Oie, T.P. Jung, C.T. Lin, L.D. Liao, and S. Makeig. Cognition in action: imaging brain/body dynamics in mobile humans. *Reviews in the Neurosciences*, 22(6):593–608, 2011.
- [GGMF11] Joseph T. Gwin, Klaus Gramann, Scott Makeig, and Daniel P. Ferris. Electro-cortical activity is coupled to gait cycle phase during treadmill walking. *NeuroImage*, 54(1289-1296), 2011.
- [GHA⁺09] Holger Gevensleben, Birgit Holl, Björn Albrecht, Claudia Vogel, Dieter Schlamp, Oliver Kratz, Petra Studer, Aribert Rothenberger, Gunther H Moll, and Hartmut Heinrich. Is neurofeedback an efficacious treatment for ADHD? A randomised controlled clinical trial. *Journal of child psychology and psychiatry, and allied disciplines*, 50(7):780–9, July 2009.
- [Git13] Kim Gittleston. How big data is changing the cost of insurance. *BBC News*, 2013.
- [GMP⁺09] Jeremy Ginsberg, Matthew H Mohebbi, Rajan S Patel, Lynnette Brammer, Mark S Smolinski, and Larry Brilliant. Detecting influenza epidemics using search engine query data. *Nature*, 457(7232):1012–1014, 2009.
- [GSS⁺14] Daniel Greenwood, Arkadiusz Stopczynski, Brian Sweatt, Thomas Hardjono, and Alex Pentland. The new realities of living in a big data society. In Julia Lane, Victoria Stodden, Stefan Bender, and Helen Nissenbaum, editors, *Big Data, Privacy, and the Public Good: Frameworks for Engagement*. Cambridge University Press, 2014.
- [Hay12] Erika Check Hayden. "informed consent: A broken contract", 2012.
- [HC12] Charline Hondrou and George Caridakis. Affective, natural interaction using eeg: sensors, application and future directions. In *Artificial Intelligence: Theories and Applications*, pages 331–338. Springer, 2012.
- [HGS07] Hartmut Heinrich, Holger Gevensleben, and Ute Strehl. Annotation: neuro-feedback - train your brain to train behaviour. *Journal of child psychology and psychiatry, and allied disciplines*, 48(1):3–16, January 2007.

- [HI94] M.S. Hämäläinen and R.J. Ilmoniemi. Interpreting magnetic fields of the brain: minimum norm estimates. *Med. Biol. Eng. Comput.*, 32:35–42, 1994.
- [Hil13] Holger Hill. Modulation of frontal and parietal neuronal activity by visuomotor learning. an erp analysis of implicit and explicit pursuit tracking tasks. *International Journal of Psychophysiology*, 2013.
- [HNL⁺04] Uri Hasson, Yuval Nir, Ifat Levy, Galit Fuhrmann, and Rafael Malach. Intersubject synchronization of cortical activity during natural vision. *science*, 303(5664):1634–1640, 2004.
- [HNP⁺04] Thilo Hinterberger, Nicolai Neumann, Mirko Pharn, Andrea Kübler, Anke Grether, Nadine Hofmayer, Barbara Wilhelm, Herta Flor, and Niels Birbaumer. A multimodal brain-based feedback and communication system. *Experimental Brain Research*, 154(4):521–526, February 2004.
- [HSD⁺05] Simon Hanslmayr, Paul Sauseng, Michael Doppelmayr, Manuel Schaubus, and Wolfgang Klimesch. Increasing individual upper alpha power by neurofeedback improves cognitive performance in human subjects. *Applied psychophysiology and biofeedback*, 30(1):DOI: 10.1007/s10484-005-2169-8, March 2005.
- [HSH13] Sofie Therese Hansen, Carsten Stahlhut, and Lars Kai Hansen. Sparse source eeg imaging with the variational garrote. In *Pattern Recognition in Neuroimaging (PRNI), 2013 International Workshop on*, pages 106–109. IEEE, 2013.
- [HSMK⁺13] Aniko Hannak, Piotr Sapiezynski, Arash Molavi Kakhki, Balachander Krishnamurthy, David Lazer, Alan Mislove, and Christo Wilson. Measuring personalization of web search. In *Proceedings of the 22nd international conference on World Wide Web*, pages 527–538. International World Wide Web Conferences Steering Committee, 2013.
- [HVG⁺07] H. Hallez, B. Vanrumste, R. Grech, J. Muscat, W. De Clercq, A. Vergult, Y. D’Asseler, K.P. Camilleri, S.G. Fabri, S. Van Huffel, et al. Review on solving the forward problem in EEG source analysis. *J of NeuroEng. and Rehab*, 4(1):46, 2007.
- [JHL⁺98] Tzyy-Ping Jung, Colin Humphries, Te-Won Lee, Scott Makeig, Martin J Mckeown, Vicente Iragui, and Terrence J Sejnowski. Removing electroencephalographic artifacts: comparison between ica and pca. In *Neural Networks for Signal Processing VIII, 1998. Proceedings of the 1998 IEEE Signal Processing Society Workshop*, pages 63–72. IEEE, 1998.
- [JLJ⁺10] B.S. Jensen, Jakob Eg Larsen, K. Jensen, J. Larsen, and Lars Kai Hansen. Estimating human predictability from mobile sensor data. In *Machine Learning for Signal Processing (MLSP), 2010 IEEE International Workshop on*, pages 196–201. IEEE, 2010.
- [JMH⁺00] Tzyy-Ping Jung, Scott Makeig, Colin Humphries, Te-Won Lee, Martin J Mckeown, Vicente Iragui, and Terrence J Sejnowski. Removing electroencephalographic artifacts by blind source separation. *Psychophysiology*, 37(2):163–178, 2000.
- [Jol02] Ian T. Jolliffe. *Principal Component Analysis*. Springer Series in Statistics. Springer, 1986 (2002).
- [KBD⁺10] N. Kiukkonen, J. Blom, O. Dousse, D. Gatica-Perez, and J. Laurila. Towards rich mobile phone datasets: Lausanne data collection campaign. *Proc. ICPS, Berlin*, 2010.
- [KBH⁺02] Andreas Keil, Margaret M Bradley, Olaf Hauk, Brigitte Rockstroh, Thomas Elbert, and Peter J Lang. Large-scale neural correlates of affective picture processing. *Psychophysiology*, 39(5):641–649, 2002.

- [KD65] Hans H Kornhuber and Lüder Deecke. Hirnpotentialänderungen bei willkürbewegungen und passiven bewegungen des menschen: Bereitschaftspotential und reafferente potentiale. *Pflüger's Archiv für die gesamte Physiologie des Menschen und der Tiere*, 284(1):1–17, 1965.
- [KHFK07] Apu Kapadia, Tristan Henderson, Jeffrey Fielding, and David Kotz. Virtual walls: Protecting digital privacy in pervasive environments. *Pervasive Computing*, pages 162–179, 2007.
- [KHHK99] Clare-Marie Karat, Christine Halverson, Daniel Horn, and John Karat. Patterns of entry and correction in large vocabulary continuous speech recognition systems. In *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*, pages 568–575. ACM, 1999.
- [Kli99] W Klimesch. EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain research. Brain research reviews*, 29(2-3):169–95, April 1999.
- [KN11] Juuso Karikoski and Matti Nelimarkka. Measuring social relations with multiple datasets. *International Journal of Social Computing and Cyber-Physical Systems*, 1(1):98–113, 2011.
- [Kva12] Stian Pedersen Kvaale. Emotion recognition in eeg: A neuroevolutionary approach. 2012.
- [KVP05] Julien Kronegg, Sviatoslav Voloshynovskiy, and Thierry Pun. Analysis of bit-rate definitions for brain-computer interfaces. In *Csrea hci*, pages 40–46, 2005.
- [LBC⁺05] Peter J Lang, Margaret M Bradley, Bruce N Cuthbert, et al. *International affective picture system (IAPS): Affective ratings of pictures and instruction manual*. NIMH, Center for the Study of Emotion & Attention, 2005.
- [LBJ⁺99] Simon P Levine, David A Bell, Lincoln A Jaros, Richard C Simpson, Yoram Koren, and Johann Borenstein. The navchair assistive wheelchair navigation system. *Rehabilitation Engineering, IEEE Transactions on*, 7(4):443–451, 1999.
- [LDDPM13] Antonio Lima, Manlio De Domenico, Veljko Pejovic, and Mirco Musolesi. Exploiting cellular data for disease containment and information campaigns strategies in country-wide epidemics. *arXiv preprint arXiv:1306.4534*, 2013.
- [LPA⁺09] D. Lazer, A.S. Pentland, L. Adamic, S. Aral, A.L. Barabasi, D. Brewer, N. Christakis, N. Contractor, J. Fowler, M. Gutmann, et al. Life in the network: the coming age of computational social science. *Science (New York, NY)*, 323(5915):721, 2009.
- [LSHF99] Philip W Lavori, Jeremy Sugarman, Marguerite T Hays, and John R Feussner. Improving informed consent in clinical trials: a duty to experiment. *Controlled clinical trials*, 20(2):187–193, 1999.
- [LSSO95] J F Lubar, M O Swartwood, J N Swartwood, and P H O'Donnell. Evaluation of the effectiveness of EEG neurofeedback training for ADHD in a clinical setting as measured by changes in T.O.V.A. scores, behavioral ratings, and WISC-R performance. *Biofeedback and self-regulation*, 20(1):83–99, March 1995.
- [Lyo11] R. Lyons. The spread of Evidence-Poor medicine via flawed Social-Network analysis. *Statistics, Politics, and Policy*, 2, 2011.
- [MCH⁺11] Rachel Moseley, Francesca Carota, Olaf Hauk, Bettina Mohr, and Friedemann Pulvermüller. A role for the motor system in binding abstract emotional meaning. *Cerebral Cortex*, doi:10.1093/cercor/bhr238:1–14, 2011.
- [MGJ⁺09] S. Makeig, K. Gramann, T.P. Jung, T.J. Sejnowski, and H. Poizner. Linking brain, mind and behavior. *International Journal of Psychophysiology*, 73(2):95–100, 2009.

- [MGPF99] J. Müller-Gerking, G. Pfurtscheller, and H. Flyvbjerg. Designing optimal spatial filters for single-trial EEG classification in a movement task. *Clinical Neurophysiology*, 110:787–798, 1999.
- [MGWM13] Arghir-Nicolae Moldovan, Ioana Ghergulescu, Stephan Weibelzahl, and Cristina Hava Muntean. User-centered eeg-based multimedia quality assessment. In *Broadband Multimedia Systems and Broadcasting (BMSB), 2013 IEEE International Symposium on*, pages 1–8. IEEE, 2013.
- [MKHS08] H. Mahato, D. Kern, P. Holleis, and A. Schmidt. Implicit personalization of public environments using bluetooth. In *CHI'08 extended abstracts on Human factors in computing systems*, pages 3093–3098. ACM, 2008.
- [MLC⁺13] Mary Madden, Amanda Lenhart, Sandra Cortesi, Urs Gasser, Maeve Dugan, Aaron Smith, and Meredith Beaton. Teens, Social Media, and Privacy. http://www.pewinternet.org/~media/Files/Reports/2013/PIP_TeensSocialMediaandPrivacy.pdf, 2013.
- [MLF⁺08] E. Miluzzo, N.D. Lane, K. Fodor, R. Peterson, H. Lu, M. Musolesi, S.B. Eisenman, X. Zheng, and A.T. Campbell. Sensing meets mobile social networks: the design, implementation and evaluation of the cenceme application. In *Proceedings of the 6th ACM conference on Embedded network sensor systems*, pages 337–350. ACM, 2008.
- [MRMP⁺10] J d R Millán, Rüdiger Rupp, Gernot R Müller-Putz, Roderick Murray-Smith, Claudio Giugliemma, Michael Tangermann, Carmen Vidaurre, Febo Cincotti, Andrea Kübler, Robert Leeb, et al. Combining brain–computer interfaces and assistive technologies: state-of-the-art and challenges. *Frontiers in neuroscience*, 4, 2010.
- [MS94] Lutz Molgedey and Heinz Georg Schuster. Separation of a mixture of independent signals using time delayed correlations. *Physical review letters*, 72(23):3634, 1994.
- [MU12] Alexis Morris and Mihaela Ulieru. Friends: Brain-monitoring agents for adaptive socio-technical systems. *Multiagent and Grid Systems*, 8(4):329–347, 2012.
- [NKK⁺03] Nicolai Neumann, Andrea Kübler, Jochen Kaiser, Thilo Hinterberger, and Niels Birbaumer. Conscious perception of brain states: mental strategies for brain-computer communication. *Neuropsychologia*, 41(8):1028–1036, January 2003.
- [NKM08] Q. Noirhomme, R.I. Kitney, and B. Macq. Single-trial eeg source reconstruction for brain–computer interface. *Biomedical Engineering, IEEE Transactions on*, 55(5):1592–1601, 2008.
- [NMC98] Jack B Nitschke, Gregory A Miller, and Edwin W Cook. Digital filtering in eeg/erp analysis: Some technical and empirical comparisons. *Behavior Research Methods, Instruments, & Computers*, 30(1):54–67, 1998.
- [NS10] Christopher M. Niel and Michael P. Stryker. Modulation of visual responses by behavioral state in mouse visual cortex. *Neuron*, 65:472–479, 2010.
- [OBM05] Daniel Olgun Olgun, Frantz Bouchereau, and Sergio Martinez. Adaptive notch filter for eeg signals based on the lms algorithm with variable step-size parameter. In *Conference on Information Sciences and Systems, The Johns Hopkins University*, 2005.
- [OSH⁺07] J-P Onnela, Jari Saramäki, Jorkki Hyvönen, György Szabó, David Lazer, Kimmo Kaski, János Kertész, and A-L Barabási. Structure and tie strengths in mobile communication networks. *Proceedings of the National Academy of Sciences*, 104(18):7332–7336, 2007.
- [Pen09] Alex Pentland. Reality mining of mobile communications: Toward a new deal on data. *The Global Information Technology Report 2008–2009*, page 1981, 2009.

- [PF10] Friedemann Pulvermüller and Luciano Fadiga. Active perception: sensorimotor circuits as a cortical basis for language. *Nature Neuroscience*, 11:351–360, May 2010.
- [PFF⁺92] Giuseppe di Pellegrino, Luciano Fadiga, Leonardo Fogassi, Vittorio Gallese, and Giacomo Rizzolati. Understanding motor events: a neurophysiological study. *Experimental Brain Research*, 91:176–180, 1992.
- [PLdS99] Gert Pfurtscheller and Fernando H Lopes da Silva. Event-related eeg/meg synchronization and desynchronization: basic principles. *Clinical neurophysiology*, 110(11):1842–1857, 1999.
- [PMML94] R. D. Pascual-Marqui, C. M. Michel, and D. Lehmann. Low resolution electromagnetic tomography: a new method for localizing electrical activity in the brain. *Int J. Psychophysiol.*, 18:49–65, 1994.
- [POTB03] Michael K Paasche-Orlow, Holly A Taylor, and Frederick L Brancati. Readability standards for informed-consent forms as compared with actual readability. *New England journal of medicine*, 348(8):721–726, 2003.
- [PRF02] C. Phillips, M.D. Rugg, and K.J. Friston. Anatomically Informed Basis Functions for EEG Source Localisation: Combining Functional and Anatomical Constraints. *NeuroImage*, 16(3):678–695, 2002.
- [PSS⁺11] Michael Kai Petersen, Carsten Stahlhut, Arkadiusz Stopczynski, Jakob Eg Larsen, and Lars Kai Hansen. Smartphones get emotional: mind reading images and reconstructing the neural sources. In *Affective Computing and Intelligent Interaction*, pages 578–587. Springer, 2011.
- [PSV01] Romualdo Pastor-Satorras and Alessandro Vespignani. Epidemic spreading in scale-free networks. *Physical review letters*, 86(14):3200, 2001.
- [Puh13] Jan Puhl. Silicon savannah: Africa’s transformative digital revolution, 2013.
- [QHMST13] Melissa Quek, Johannes Höhne, Roderick Murray-Smith, and Michael Tangermann. Designing future bcis: Beyond the bit rate. In *Towards Practical Brain-Computer Interfaces*, pages 173–196. Springer, 2013.
- [RS10] Giacomo Rizzolati and Corrado Sinigaglia. The functional role of the parieto-frontal mirror circuit: interpretations and misinterpretations. *Nature*, 11:264–274, April 2010.
- [RST11] Tyler Rolheiser, Emmanuel A. Stamatakis, and Lorraine K. Tyler. Dynamic processing in the human language system: Synergy between the arcuate fascicle and extreme capsule. *The Journal of Neuroscience*, 31(47):16949–16957, 2011.
- [Rus80] James A Russell. A circumplex model of affect. *Journal of personality and social psychology*, 39(6):1161, 1980.
- [RZZB12] Gyan Ranjan, Hui Zang, Zhi-Li Zhang, and Jean Bolot. Are call detail records biased for sampling human mobility? *ACM SIGMOBILE Mobile Computing and Communications Review*, 16(3):33–44, 2012.
- [SAS⁺12] Carsten Stahlhut, Hagai Thomas Attias, Arkadiusz Stopczynski, Michael Kai Petersen, Jakob Eg Larsen, and Lars Kai Hansen. An evaluation of eeg scanner’s dependence on the imaging technique, forward model computation method, and array dimensionality. In *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*, pages 1538–1541. IEEE, 2012.
- [SF12] Luca Szegetes and Bertalan Forstner. Towards biofeedback-controlled self-rewarding learning with mobile devices. In *Cognitive Infocommunications (CogInfoCom), 2012 IEEE 3rd International Conference on*, pages 303–308. IEEE, 2012.

- [SF13] Luca Szegletes and Bertalan Forstner. Reusable framework for the development of adaptive games. In *Cognitive Infocommunications (CogInfoCom), 2013 IEEE 4th International Conference on*, pages 601–606. IEEE, 2013.
- [SGHP14] A. Stopczynski, D. Greenwood, L. K. Hansen, and A. Pentland. Privacy for Personal Neuroinformatics. *ArXiv e-prints*, March 2014.
- [SHCN08] Semyon Slobounov, Mark Hallett, Cheng Cao, and Karl Newell. Modulation of cortical activity as a result of of voluntary postural sway direction: an eeg study. *Neuroscience Letters*, 442(3):doi:10.1016/j.neulet.2008.07.021, 2008.
- [Sho06] Donald C Shoup. Cruising for parking. *Transport Policy*, 13(6):479–486, 2006.
- [Sim03] Laura A Siminoff. Toward improving the informed consent process in research with humans. *IRB: Ethics and Human Research*, 25(5):S1–S3, 2003.
- [SJWH04] Harald T Schupp, Markus Junghöfer, Almut I Weike, and Alfons O Hamm. The selective processing of briefly presented affective pictures: An erp analysis. *Psychophysiology*, 41(3):441–449, 2004.
- [SMP⁺99] Jeremy Sugarman, Douglas C McCrory, Donald Powell, Alex Krasny, Betsy Adams, Eric Ball, and Cynthia Cassell. Empirical research on informed consent: an annotated bibliography. *Hastings Center Report*, 29(1):s1–s42, 1999.
- [SPP⁺14] Arkadiusz Stopczynski, Riccardo Pietri, Alex Pentland, David Lazer, and Sune Lehmann. Privacy in Sensor-Driven Human Data Collection: A Guide for Practitioners. *ArXiv e-prints*, March 2014.
- [SSL⁺11] C. Stahlhut, A. Stopczynski, J. E. Larsen, M. K. Petersen, and L. K. Hansen. A smartphone functional brain scanner, 2011.
- [SSL⁺14] Arkadiusz Stopczynski, Carsten Stahlhut, Jakob Eg Larsen, Michael Kai Petersen, and Lars Kai Hansen. The smartphone brain scanner: A portable real-time neuroimaging system. *PLoS ONE*, 9(2):e86733, 02 2014.
- [SSP⁺13] Arkadiusz Stopczynski, Carsten Stahlhut, Michael Kai Petersen, Jakob Eg Larsen, Camilla Falk Jensen, Marieta Georgieva Ivanova, Tobias S Andersen, and Lars Kai Hansen. Smartphones as pocketable labs: Visions for mobile brain imaging and neurofeedback. *International Journal of Psychophysiology*, 2013.
- [SSS⁺14] Arkadiusz Stopczynski, Vedran Sekara, Piotr Sapiezynski, Andrea Cuttone, Mette My Madsen, Jakob Eg Larsen, and Sune Lehmann. Measuring large-scale social networks with high resolution. *arXiv preprint arXiv:1401.7233*, 2014.
- [ST11] C.R. Shalizi and A.C. Thomas. Homophily and contagion are generically confounded in observational social network studies. *Sociological Methods & Research*, 40(2):211–239, 2011.
- [SvGOH10] Irina Simanova, Marcel van Gerven, Robert Oostenveld, and Peter Hagoort. Identifying object categories from event-related eeg: toward decoding of conceptual representations. *PloS one*, 5(12):e14465, 2010.
- [Swa12] Melanie Swan. Sensor mania! the internet of things, wearable computing, objective metrics, and the quantified self 2.0. *Journal of Sensor and Actuator Networks*, 1(3):217–253, 2012.
- [Swa13] Melanie Swan. The quantified self: Fundamental disruption in big data science and biological discovery. *Big Data*, 1(2):85–99, 2013.
- [TCD⁺10] Eran Toch, Justin Cranshaw, Paul Hanks, Drielsma, Janice Y Tsai, Patrick Gage Kelley, James Springfield, Lorrie Cranor, Jason Hong, and Norman Sadeh. Empirical models of privacy in location sharing. In *Proceedings of the 12th ACM international conference on Ubiquitous computing*, pages 129–138, 2010.

- [TN13] Aruna Tyagi and Vijay Nehra. Brain–computer interface: a thought translation device turning fantasy into reality. *International Journal of Biomedical Engineering and Technology*, 11(2):197–211, 2013.
- [U⁺92] George J Annas Edward R Utley et al. *The Nazi Doctors and the Nuremberg Code: Human Rights in Human Experimentation: Human Rights in Human Experimentation*. Oxford University Press, 1992.
- [VEC⁺03] David Vernon, Tobias Egner, Nick Cooper, Theresa Compton, Claire Neilands, Amna Sheri, and John H Gruzelier. The effect of training distinct neurofeedback protocols on aspects of cognitive performance. *International Journal of Psychophysiology*, 47(1):75–85, January 2003.
- [VS12] C. Vi and S. Subramanian. Detecting error-related negativity for interaction design. In *Proceedings of the 2012 ACM annual conference on Human Factors in Computing Systems*, pages 493–502. ACM, 2012.
- [WHD97] Julie Weston, Mary Hannah, and Julia Downes. Evaluating the benefits of a patient information video during the informed consent process. *Patient education and counseling*, 30(3):239–245, 1997.
- [WKM⁺07] CH Wolters, H. Kostler, C. Moller, J. Hardtlein, L. Grasedyck, and W. Hackbusch. Numerical mathematics of the subtraction method for the modeling of a current dipole in EEG source reconstruction using finite element head models. *SIAM J. Sci. Comp.*, 30(1):24–45, 2007.
- [WMD⁺09] Jonathan Woetzel, Lenny Mendonca, Janamitra Devan, Stefano Negri, Yangmel Hu, Luke Jordan, Xiujun Li, Alexander Maasry, Geoff Tsen, and Flora Yu. Preparing for china’s urban billion. 2009.
- [Yas09] Y. Yasui. A brainwave signal measurement and data processing technique for daily life applications. *Journal of physiological anthropology*, 28(3):145–150, 2009.
- [ZHH11] Benedikt Zoefel, René J Huster, and Christoph S Herrmann. Neurofeedback training of the upper alpha frequency band in EEG improves cognitive performance. *NeuroImage*, 54(2):1427–31, January 2011.
- [ZK11] Thorsten O Zander and Christian Kothe. Towards passive brain–computer interfaces: applying brain–computer interface technology to human–machine systems in general. *Journal of Neural Engineering*, 8(2):025005, 2011.